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The Role of Health Policy in Improving Access to Substance Use Disorder Treatment, Influencing Substance Use, and Promoting Public Safety

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An abstract of
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James T. Laney School of Graduate Studies of Emory University
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Abstract

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In the United States, substance use has historically been treated as a legal and moral issue that deserves to be punished rather than a public health issue that can be effectively treated. However, the ongoing implementation of the Affordable Care Act (ACA) and the Mental Health Parity and Addiction Equity Act (MHPAEA) has presented opportunities for people in need of substance use disorder (SUD) treatment to gain access to treatment. This dissertation seeks to provide rigorous evidence on the potential of health policy levers and financial incentives to encourage treatment seeking, reduce criminal involvement, and influence substance use behaviors. The three essays of my dissertation examine: the impact of insurance expansions and regulations on improving SUD treatment use; the potential spillovers of improved SUD treatment use on reducing substance-related violent and property crimes; and the implications of liberalizing drug laws for substance use.

The findings of this dissertation provide evidence that, through improving coverage for SUD treatment, insurance expansions and regulations can effectively improve access to SUD treatment. Improved access to treatment, in turn, can effectively and cost-effectively promote public safety by reducing substance use-related crimes. The findings also add a caution that simply liberalizing drug laws may have unintended consequences for a certain range of substance use outcomes that are interrelated and sensitive to policy shocks. Thus, drug liberalization policies should be designed with public health concerns in mind and paired with additional public health strategies to mitigate an undesirable surge in substance use.

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CHAPTER 1: Introduction

In the United States, substance use has been historically treated as a legal and moral issue that deserves to be punished rather than a public health issue that can be effectively treated. Criminalization has been the dominant element of substance control regime since the Controlled Substance Act (CSA) was enacted into law in 1970 and President Nixon declared the "war on drugs" in the following year. Despite the tough punitive policies, the United States continues to lead the world in substance use problems (Degenhardt, 2008). Substance use in the United States remains a serious threat to productivity, health, and public safety, and has become a significant drain on the economy. In 2008 alone, excessive alcohol use and illicit drug use costs our nation more than $400 billion in lost productivity, health care expenses and crime costs (Rehm, et al., 2009; NDIC, 2011).

In his 2013 speech to the American Bar Association's House of Delegates, Attorney General Eric Holder called for a "sweeping, systemic change" to the "ineffective and unsustainable" drug war regime, and laid out a new agenda for public safety reform. The centerpiece of Holder's new agenda is to scale back mandatory minimum sentences for low-level drug offenders, and to replace the incarceration with treatment for substance use. Conservatives have expressed concerns, however, that relaxing criminal sanctions for substance use would exacerbate the current situation by undermining the role of punishment in preventing individuals from substance use and protecting society against substance-related accidents and crimes.

Parallel with the proposed agenda for public safety reform is the ongoing implementation of health care reform. In January 2014, two major expansion-related provisions of the Affordable Care Act (ACA) came into effect. These ACA provisions are the expansion of Medicaid and the creation of Health Insurance Marketplaces (formerly known as "exchanges"). The target low-income adult population for Medicaid expansions and Marketplaces under the ACA has a disproportionally high prevalence of substance use disorder (SUD) and large unmet needs for SUD treatment. Subject to federal parity legislation (i.e., Mental Health Parity and Addiction Equity Act, MHPAEA) adopted in 2008, Medicaid and Marketplace plans are required to provide SUD benefits for the expanded enrollees on par with comparable medical/surgical benefits. Many behavioral health experts and advocates, therefore, anticipate a transformative power of these insurance expansions and regulations in reducing financial barriers to SUD treatment among those in need of the treatment. Nonetheless, it remains unclear whether this vulnerable segment of the population would see tangible gains in health coverage and access to SUD treatment as a result of health care reform, and to what extent the individual gains in coverage and access would translate into broader social benefits such as public safety enhancement.

To inform discussions surrounding the future direction of the nation's health care reform and public safety reform, the three essays in my study examine: (i) the impact of insurance expansions and regulations on improving access to SUD treatment; (ii) the potential spillovers of improved access to SUD treatment on reducing substance-related violent and property crimes; and (iii) the behavioral implications of liberalizing drug laws. (Figure 1.1)

The first essay examines the impact of insurance regulations on improving access to SUD treatment (Robinson, Whitter, and Magaña, 2006). I focus on a set of regulatory policies in state group health insurance markets referred to as “state SUD parity mandates”. These parity mandates are designed to reduce the discriminatory cost sharing and treatment limitations faced by those in need of SUD treatment. By assessing the SUD parity mandates in ten states between 2000 and 2008, I find a positive effect of the implementation and comprehensiveness of these state SUD parity mandates on state-aggregate SUD treatment rates. These findings shed light on the potential of the recent federal parity legislation for improving access to SUD treatment on a national scale.

The second essay builds on the first and examines the potential spillovers of improved access to SUD treatment on reducing violent and property crimes. I establish a causal relationship between the exogenous improvement in county-level SUD treatment rates induced by state insurance expansions and regulations (i.e., Health Insurance Flexibility and Affordability (HIFA)-waiver expansions and SUD parity mandates) and reductions in the rates of three types of crimes (i.e., robbery, aggravated assault, and larceny theft). These economically meaningful crime-reduction effects suggest that improving access to SUD treatment for those who may otherwise be on the margins of criminal involvement is likely to be an effective and cost-effective investment in public safety.

In the third essay, I examine the behavioral and public health implications of drug liberalization, in the context of U.S. marijuana reform. I estimate the effect of medical marijuana laws (MMLs) in ten states between 2004 and 2012 on a variety of substance use outcomes in both adolescent and adult populations. This study provides evidence for a significant effect of MML implementation on increasing marijuana use, binge drinking and simultaneous use of marijuana and alcohol among adults of legal drinking age. The results do not, however, lend support for a spillover effect of MMLs on other types of substance use behaviors such as underage drinking, pain medication misuse, and hard drug use.

Taken together, the three essays of this dissertation offer new insights into the importance of health policies in the nation's substance control regime in terms of improving access to SUD treatment, promoting public safety, and influencing substance use. The study findings provide evidence that, through improving coverage for SUD treatment, insurance expansions and regulations (e.g., Medicaid expansions and SUD parity mandates) can effectively improve access to SUD treatment. The improved access, in turn, can effectively and cost-effectively reduce substance use-related crimes. My findings also add a caution that simply liberalizing drug laws and relaxing the criminalization regime may have unintended consequences for a certain range of substance use behaviors that are interrelated and sensitive to policy changes. Thus, drug liberalization policies should be designed with public health concerns in mind and paired with additional public health strategies to mitigate an undesirable surge in substance use.

1.1 Introduction to Essay 1: State Parity Laws and Access to Treatment for Substance Use Disorder in the United States

1.1.1 Motivation of Essay 1

An estimated 23 million Americans suffered from SUDs in 2010. Among those who needed SUD treatment, only 17% received any treatment for their condition, and 11% received treatment in a specialty setting. Limited insurance benefits for SUD poses a major financial barrier to SUD treatment among those perceiving a need for treatment (SAMHSA, 2011; Bouchery, et al., 2012; Amaro, 1999).

SUD parity mandate is designed to improve access to SUD treatment by correcting the discriminatory cost sharing and treatment limitations imposed on SUD treatment. During the past decades, more than one-half of states in the U.S. have enacted such laws to mandate that group health plans should provide insurance benefits for SUD treatment on par with those for comparable medical/surgical treatment (Robinson, Whitter, and Magaña, 2006). More recently, the passage of the Mental Health Parity and Addiction Equity Act (MHPAEA) and the Affordable Care Act (ACA) incorporated SUD parity mandate into the federal legislation, and extended the mandate to a full range of private and public health plans (Busch, 2012; Barry and Huskamp, 2011).

Beyond the symbolic value towards equitable coverage, it is important to ask whether SUD parity has a substantive impact on improving access to SUD treatment. The first essay addresses this question by examining the effect of state SUD parity mandates on state-level SUD treatment rates between 2000 and 2008.

1.1.2 Conceptual Framework and Hypotheses of Essay 1

My conceptual framework draws upon the behavioral model developed by Andersen and colleagues (Andersen 1968; Andersen, Newman, 1973; Andersen, 1995). Andersen's behavioral model provides a holistic perspective to integrate a range of individual and societal determinants of access to care. The initial behavioral model, described in a 1968 research monograph, includes three major components of individual determinants: (i) predisposing factors; (ii) enabling factors; and (iii) need factors (Andersen, 1968). Contextual determinants were added shortly afterwards in a widely cited journal article, and were defined as the policy environment and delivery system within which treatment is provided and received. (Andersen and Newman, 1973; Andersen, 1995) These contextual factors can affect access to care by affecting individuals' enabling factors and need factors (Andersen, 1995; Phillips, et al., 1998). The focus of my analysis is on one of the contextual determinants, health policy. More specifically, my focal policy is a set of state SUD parity mandates that mandate the insurance benefits for SUD treatment to be offered on par with those for comparable medical/surgical treatment. (Robinson, Whitter, and Magaña, 2006). (Figure 1.2)

In his seminal work in 1989, Summers articulates two arguments for using an insurance mandate to correct market failures and ensure certain benefits are provided without imposing welfare loss (Summers, 1989). The first argument for an insurance mandate is that individuals may undervalue certain insurance benefits due to positive externalities or time-inconsistent preference (i.e., internality). In the case of SUD benefits, stigma related to addiction and self-control problems may give rise to the undervaluation of the benefits. Summers' second argument for an insurance mandate is that risk heterogeneity and asymmetric information may result in a market where employers and insurers compete to attract only the "good" risks by reducing or removing certain benefits. Under these circumstances, even if SUD benefits are fully valued by individuals, employers may still shy away from offering the benefits for the fear of attracting workers with SUD.

In a market with either of these two types of market failures (i.e., "merit good" and "adverse selection"), an insurance mandate can be used to improve the market efficiency by "forcing" people to have SUD benefits that more closely approximate what they would have had if the market had been functioning well (Summers, 1989). According to Summers' key insight into the insurance market and mandate, SUD parity should have the potential for correcting the market failures that have undermined the potential *need* and financial *ability* of individuals with SUD. Consequently, we may see an improvement in the market efficiency when state SUD parity mandates allow people to realize their demand for SUD treatment that contribute to individual utility and social welfare. Furthermore, states differ in their interpretation of "parity", which leads to differences in the comprehensiveness of the parity mandates they implement. Accordingly, we may also see heterogeneous effects across state SUD parity mandates with different levels of comprehensiveness.

Therefore, this study tests the following hypotheses:

H_1: The implementation of state SUD parity mandates increases the use of SUD treatment.

H_2: The increase in SUD treatment use is more pronounced among those with more comprehensive SUD parity mandates.

In addition to health policy as an important contextual determinant, Andersen's behavioral model also gives attention to other contextual-level enabling factors such as the insurance and economic status of populations, as well as the capacity of delivery system. The model also touches on contextual-level need factors and predisposing factors such as prevalence of the condition and sociodemographic composition. In my study, these contextual factors may be correlated with states' decisions to implement SUD parity mandates or to exempt certain groups from the mandates. They may also be correlated with individual need and ability to receive SUD treatment (Pacula and Sturm, 1999; Pacula and Sturm, 2000; Sturm and Sherbourne, 2001; Buchmueller, et al., 2007; Buck, 2011).

1.1.3 Data and Methods of Essay 1

The main source of data is the National Survey of Substance Abuse Treatment Services (N-SSATS) 2000, 2002-2008, which provides facility-level information on specialty SUD treatment. The N-SSATS facility universe covers all known specialty SUD treatment facilities, allowing for a nearly complete enumeration of specialty SUD treatment services in the United States. Throughout the study period, response rates range from 92 percent to 95 percent.

The facility-level data from N-SSATS are aggregated to the state-level to create an analytic panel of 392 state-year observations across the 49 states and eight years.[1] Select

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[1] Note: Virginia was excluded from the analysis because it was the only state that moved away from parity when full parity was repealed and regressed to partial parity in 2004.

state-level measures for SUD prevalence, sociodemographic composition, health insurance market and economic conditions, as well as the capacity of delivery system are merged with N-SSATS from nationally representative datasets. The data sources are National Survey of Drug Use and Health (NSDUH), Treatment Improvement Exchange (TIE), Population Estimates Program (PEP), Current Population Survey (CPS), Current Population Survey-Annual Social and Economic Supplement (CPS-ASEC), and Statistics of United States Businesses (SUSB).

A quasi-experimental difference-in-differences (DD) design is used to estimate the effect of state SUD parity mandates on state-aggregate SUD treatment rates (i.e., annual number of entries into specialty SUD treatment facilities per 1,000 state residents). The DD design is operationalized through state and year two-way fixed effects. This two-way fixed-effect approach helps distinguish the 'real' policy effect of SUD parity mandates from the time-invariant state heterogeneity as well as the national secular trend and common shocks in treatment rates that are systematically correlated with the parity mandates (Wooldridge, 2002).

$$\boldsymbol{SUDTrt_{s,t}} = \beta_0 + \beta_1 \boldsymbol{Parity_{s,t}} + \upsilon_s + \tau_t + \beta_2 X_{s,t} + \varepsilon_{s,t}$$

$$\boldsymbol{SUDTrt_{s,t}} = \beta_0 + \beta_1 \boldsymbol{FullParity_{s,t}} + \beta_2 \boldsymbol{PartialParity_{s,t}} + \beta_3 \boldsymbol{ParityIfOffered_{s,t}} + \upsilon_s + \tau_t + \beta_4 X_{s,t} + \varepsilon_{s,t}$$

Two model specifications are estimated. The first model estimates the SUD treatment rate at state *s* in year *t* ($SUDTrt_{s,t}$) as a function of a dichotomous indicator of SUD parity implementation ($Parity_{s,t}$), the state fixed effect (υ_s), the year fixed effect (τ_t), a state-level time-variant covariates vector including SUD prevalence, sociodemographic composition, insurance and economic status, and a proxy for the capacity of delivery system ($X_{s,t}$), and an idiosyncratic error term ($\varepsilon_{s,t}$). In the second model, the dichotomous indicator of any SUD parity implementation ($Parity_{s,t}$) is replaced with the categorical variable of the comprehensiveness in parity mandates ($FullParity_{s,t}$, $PartialParity_{s,t}$, *and* $ParityIfOffered_{s,t}$).

All estimated standard errors are clustered at the state level to correct for serial correlation that otherwise would lead to false rejections of the null hypothesis in a DD framework. The state-clustered standard errors allow for arbitrary within-state correlation in error terms but assume independence across the states (Bertrand, Duflo, and Mullainathan, 2004).

1.2 Introduction to Essay 2: The Effect of Substance Use Disorder Treatment Use on Crime

1.2.1 Motivation of Essay 2

Contemporary criminological theories suggest a causal relationship from substance use to crime, among which the most influential is Goldstein's tripartite model. (Goldstein, 2003) Goldstein provided three hypotheses to explain how substance use causes violent and property crimes. First, the pharmacological hypothesis states that violence may occur as a direct result of the intoxication of substance, either by triggering violent offense or by facilitating violent victimization. Second, the economic motivation hypothesis states that substance users and addicts commit income-generating crimes to finance their substance use habits, particularly among young people and those with low income from legal activities. A third hypothesis, the institutional hypothesis, states that being involved in the illegal drug market can expose one to an increased risk of criminal involvement (Goldstein, 2003).

If substance use is indeed on the causal pathway to crime, interventions to reduce substance use should also reduce crimes. Nonetheless, empirical studies on prohibition and the "war on drugs" suggest that these punitive approaches to substance control have not led to any significant reduction in crimes (Miron, 1999; Kuziemko and Levitt, 2004; Markowitz, 2005). I explore an alternative approach that has garnered relatively little attention in the economic literature on crime reduction, namely SUD treatment (Gerstein and Lewin, 1990; Leshner, 1999). My second essay builds on the first essay and examines the reduced-form effect of increasing access to SUD treatment on reducing crimes, assuming that this reduced-form crime-reduction effect comes largely from the structural effect through reducing substance use.

1.2.2 Conceptual Framework and Hypotheses of Essay 2

My conceptual framework, though motivated by the intuition of Goldstein's tripartite model, draws more directly upon Becker's rational choice model of crime (Becker, Murphy, and Grossman, 2006). Based on Becker's model, I specify the following structural relationship between substance use and crime:

$$\boldsymbol{Crime_{i,j,t}} = f(\boldsymbol{SubUse_{i,j,t}}, \boldsymbol{SubUse_{i',j,t}}, Enforcement_{j,t}, X1_{i,j,t}, X2_{i',j,t}, Z1_{j,t})$$

In the structural equation, criminal offense or victimization is a function of substance use by the potential perpetrator $SubUse_{i,j,t}$, substance use by the potential victim $SubUse_{i',j,t}$, law enforcement resources $Enforcement_{j,t}$, other observed and unobserved individual factors associated with the propensity for criminal offense $X_{1\ i,j,t}$ and the propensity for criminal victimization $X_{2\ i',j,t}$, as well as observed and unobserved contextual factors $Z_{1\ j,t}$ that help create or limit opportunities for crime (Becker, Murphy, and Grossman, 2006).

Instead of estimating a structural effect of substance use on crime, my empirical study estimates the reduced-form effect of increasing SUD treatment use on reducing crimes. Although I cannot explicitly estimate substance use, I assume that this reduced-form effect of increasing SUD treatment use on reducing crime comes mainly from a reduction in substance use. While my approach does not provide a direct estimate of the amount of crime that arises from more substance use problems, it provides a direct answer to the policy question of how much crime would be reduced by higher levels of SUD treatment use. Based on the estimated crime reduction effect of increasing SUD treatment use, further cost-benefit comparisons can be drawn between SUD treatment and other crime-reduction policies.

Systematic differences in the distribution of SUD treatment and crime may be observed across areas that differ in sociodemographic, economic and law enforcement factors, as well as budgetary resources and regulatory environments. Moreover, some unobserved factors may also be correlated both with SUD treatment and with crime. Of particular concern are the unobserved variations in substance use prevalence and fluctuations in market prices and purity (Caulkins and Reuter, 1998). In addition to the causal effect of SUD treatment on crime, reverse causality may also exist from crime to SUD treatment through drug courts or diversion programs offered to a select group of low-level offenders in need of the treatment (Chandler, Fletcher, and Volkow, 2009). The possibility of omitted variables and reverse causality requires rigorous identification strategies. Otherwise the crime reduction effect of SUD treatment use can be seriously underestimated. (Figure 1.3)

The following hypotheses can be drawn upon this conceptual framework:

H_3: Increasing SUD treatment use leads to reductions in crimes.

H_4: The crime-reduction effect is concentrated in low-level personal violence that can be attributed to intoxication (Goldstein's "pharmacological hypothesis") and acquisitive crimes that may largely be driven by a need to finance substance use habits ("economic motivation hypothesis").

1.2.3 Data and Methods of Essay 2

The data for this study comprises a panel of annual, county-level observations between 2001 and 2008. Primary data sources are the Uniform Crime Reports (UCR), the National Survey of Substance Abuse Treatment Services (N-SSATS). Supplementary data sources include the Area Health Resource File (AHRF), the Alcohol Policy Information System (APIS) and the Treatment Improvement Exchange (TIE) database, which, collectively, provide information on important local-level socioeconomic and policy context.

The samples for the main analysis are: (i) an unbalanced panel consisting of all 23,537 non-missing observations of 3,016 counties over an average of 7.8 years, and (ii) a balanced panel limited to 22,328 observations of 2,791 counties that had all data available over the 8-year period. Note that although the main unit of analysis is county-year, it may be too small to capture the potential area where people engage in SUD treatment and crime. To check the robustness of the county-level analyses, I also aggregate the data to a higher level, the Core-Based Statistical Area[2] (CBSA) level. Two CBSA-level samples are an unbalanced panel of 981 CBSA-like units over 7.9 years and a balanced panel of 928 CBSA-like units over 8 years.[3]

The main analysis of this study estimates the effect of county-level SUD treatment rate (i.e., annual number of entries into all known specialty SUD treatment facilities per 1,000 county residents) on county-level crime rates (i.e., the number of "index crimes" reported to the police of all law enforcement agencies per 1,000 county residents). The rates of "index crime" categories are assess separately, which include four violent crimes, namely criminal homicide, forcible rape, aggravated assault and robbery, as well as four property crimes, namely burglary, larceny theft, motor vehicle theft, and arson (Gove, Hughes, and Geerken, 1985).

$$\boldsymbol{SUDTrt_{c,s,t}} = \alpha_0 + \alpha_1\, \boldsymbol{HIFA_{s,t}} + \alpha_2\, \boldsymbol{Parity_{s,t}} + \rho_c + \tau_t + \alpha_3\, X_{1\,c,s,t} + \alpha_4\, X_{2\,s,t} + \varepsilon_{c,s,t}$$

$$\boldsymbol{Crime_{c,s,t}} = \beta_1 + \beta_2\, \boldsymbol{\widehat{SUDTrt}_{c,s,t}} + \rho_c + \tau_t + \beta_3\, X_{1\,c,s,t} + \beta_4\, X_{2\,s,t} + \varepsilon_{c,s,t}$$

Two-stage least squares-instrumental variable (TSLS-IV) analysis is used to address the endogeneity of the SUD treatment rate with respect to crime rates. In the first

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[2]A CBSA is a geographic area defined by the Office of Management and Budget (OMB) based around an urban center of at least 10,000 residents and adjacent areas that are socioeconomically tied to the urban center as determined by commuting patterns. The term "CBSA" refers collectively to both metropolitan statistical areas (MSAs) and micropolitan statistical areas (μSAs).

[3]The CBSA-level analysis excludes 1354 non-CBSA rural counties that only account for 4 percent of SUD treatment and 6 percent of crime.

stage, the county-level SUD treatment rate ($SUDTrt_{c,s,t}$) is treated as endogenous and instrumented with state-level policy indicators for HIFA-waiver expansions ($HIFA_{s,t}$) and SUD parity mandates ($Parity_{s,t}$) (Atherly, et al., 2012; Wen, et al., 2013; Coughlin, et al., 2006; Dave and Mukerjee, 2011). In the second stage, the observed value of the SUD treatment rate is replaced ($SUDTrt_{c,s,t}$) with its predicted value derived from the first stage ($\widehat{SUDTrt}_{c,s,t}$).

The TSLS-IV method relies on the exogenous variation in the SUD treatment rate induced by the two policy instruments to establish, statistically, a causal relationship between the SUD treatment rate and crime rates. We can trust the TSLS-IV estimates only if the instruments we identified are strongly related to the SUD treatment rate but otherwise unrelated to crime rates (Wooldridge, 2002). Thus in both stages, models control for the time-invariant county heterogeneity as well as the national secular trend and common shocks related to the SUD treatment rate and crime rates through county and year two-way fixed effects (υ_s and τ_t). The models also control for time-varying local factors that may be correlated with the SUD treatment rate, crime rates, and the adoption of HIFA-waiver expansions or SUD parity mandates. These time-varying local factors include a county-level vector of sociodemographic compositions, economic conditions and law enforcement levels ($X_{1\ c,s,t}$) as well as a state-level vector of government expenditures on crime-related functions, beer tax rates, and the Substance Abuse Prevention and Treatment Block Grant (SAPTBG) funding ($X_{2\ s,t}$) (Atherly, et al., 2012; Wen, et al., 2013; Coughlin, et al., 2006; Dave and Mukerjee, 2011; Brame and Piquero, 2003; Cummings, et al., 2014; Wu, Kouzis, and Schlenger, 2003; Levitt, 1997). All estimated standard errors are clustered at the state level to correct for the serial correlation (Bertrand, Duflo, and Mullainathan, 2004).

1.3 Introduction to Essay 3: The Effect of Medical Marijuana Laws on Adolescent and Adult Use of Marijuana, Alcohol, and Other Substances

1.3.1 Motivation of Essay 3

A key assumption underlying the “war on drugs” regime is that threat of criminal sanctions would effectively deter people from substance use (Bentham, 1879; Becker, 1974; Piliavin, et al., 1986). This deep-rooted deterrence hypothesis has recently been challenged, especially in the case of marijuana policy (MacCoun, 1993; Donohue, Ewing, and Pelopquin, 2010). During the past two decades, marijuana use prevalence has been leveling off despite the serious legal consequences (SAMHSA, 2013). In light of the stagnant prevalence as well as a growing body of clinical evidence on marijuana’s medicinal value (Amar, 2006), many states have adopted a more tolerant approach to marijuana policy. Since 1996, when California signed the Compassionate Use Act into law (Proposition 215) and became the first state in the U.S. to permit the medical use of marijuana, a total of 23 states and the District of Columbia have passed MMLs. These laws are intended to protect patients from state prosecution for their medical marijuana use (Hoffmann and Weber, 2010). In a groundbreaking move on November 14, 2012, Colorado and Washington legalized marijuana possession for adults’ recreational use. Marijuana liberalization reform has re-entered into the mainstream debate and legislative agenda.

This study contributes to our understanding of the behavioral and public health implications of marijuana liberalization reform by examining the effect of medical marijuana laws (MMLs) implemented in ten states between 2004 and 2012 on a variety of substance use outcomes in both adolescent and adult populations.

1.3.2 Conceptual Framework and Hypotheses of Essay 3

My conceptual framework is derived from a modern deterrence theory, which builds upon classical deterrence theory and rational choice theory. Classical deterrence theory originates in the political philosophy of Bentham's utilitarianism. Assuming that human nature is hedonistic (i.e., seeking pleasure and avoiding pain), a crime is motivated by the prospect of reward, and it can be deterred by the threat of punishment (Bentham, 1879). Rational choice theory, as the core building block of neoclassical economics, was pioneered by the Chicago school of economics. The theory states that a self-interested agent makes a choice based on the maximization of the difference between the expected utility of gain and the expected utility of loss (Becker, 1974). Modern deterrence theory links the rational choice theory with the classical deterrence theory, thereby applying the economic thinking of market behavior to the topic of social deviance: a deviant behavior can be deterred through increasing the expected utility of loss to the extent that the expected utility of gain gets cancelled out (Piliavin, et al., 1986). The modern deterrence theory advances the classical deterrence theory in that it allows not only legal consequences but also alternative deterrent mechanisms, such as health risks, societal disapproval, market prices and geographic inaccessibility, to deter people from an undesirable behavior (Piliavin, et al., 1986; MacCoun, 1993).

I adapted the modern deterrence theory to examine the effect of MML implementation on a variety of substance use behaviors. I developed a "joint intoxication demand function", which assumes that an individual with the goal of intoxication chooses from a range of intoxicants (i.e., both licit substances such as alcohol and prescription drugs and illicit substances such as marijuana and hard drugs). These intoxicants differ in their anticipated effects on the individual's intoxication experience and in their expected costs composed of market prices and non-market deterrents including legal consequences, health risks, and societal disapproval. In the context of drug criminalization/liberalization, an exogenous shock to the expected costs of one intoxicant, therefore, may shift the individual demand for the target intoxicant. The shift in demand may spill over into other intoxicants through interaction between the intoxicants in individual utility function under one's budget constraint (Chaloupka and Laixuthai, 1997; Pacula, 1998).

The focal policy of my study is MMLs implemented in ten states between 2004 and 2012. A set of concurrent policy shocks during the study period concerns state decriminalization /depenalization policies. Moreover, an individual's sociodemographic status and the budgetary and regulatory environments of one's state are also important elements in the joint intoxication demand function. These confounding factors affect not only an individual's use of certain substances and their interactions, but also whether one is exposed to the deterrence-related policies and messages, how one processes and absorbs the information, and to what extent one would translate the subjective deterrence information to objective risk perception and incorporate it in cost calculations (Kilmer, et al., 2007; Pacula, et al., 2010). Age, in particular, has been considered a main contributor to different exposures to the deterrence and different perceived risks (Chu, 2014). On a related note, inclusion/exclusion of certain key MML provisions has also been shown to be one of the contributory factors in different levels of deterrence (Pacula, et al., 2015). Thus, key provisions of an MML may have different effect on substance use. Individual response to a MML provision may also be different across age groups. (Figure 1.4)

The following hypotheses can be derived from my conceptual framework:

H_5: State implementation of MMLs increases individual marijuana use.

H_6: State implementation of MMLs may lead to increases in the use of the substances whose pharmacological effect is the most similar to that of marijuana; State MML implementation can also result in decreases in other types of substance use, which, when combined with marijuana use, produces a synergistic interaction Moore, 2010.

H_7: There may be heterogeneity in the effects of MML implementation on substance use across different components of MMLs between different age groups.

1.3.3 Data and Methods of Essay 3

Nine years of cross-sectional data were pooled from the National Survey on Drug Use and Health (NSDUH) 2004-2012, a nationally and state-representative survey on substance use behavior by the U.S. civilian, noninstitutionalized population aged 12 or above. The response rates range from 73% to 76% between 2004 and 2012. To elucidate the potential age heterogeneity, the sample is stratified into two age groups, adolescents and young adults aged 12-20 (N ≈ 269,500) and adults aged 21 or above (N ≈ 323,900).

$$\boldsymbol{SubUse_{i,s,t}} = \beta_0 + \beta_1\, \boldsymbol{MML_{s,t}} + \upsilon_s + \tau_t + \upsilon_s\, \boldsymbol{t} + \beta_2\, X_{1\,i,s,t} + \beta_3\, X_{2\,s,t} + \varepsilon_{i,s,t}$$

$$\boldsymbol{SubUse_{i,s,t}} = \beta_0 + \beta_1\ \boldsymbol{Pain_{s,t}} + \beta_1\ \boldsymbol{Registry_{s,t}} + \beta_1\ \boldsymbol{Dispensary_{s,t}} + \beta_1\ \boldsymbol{Home_{s,t}} + \upsilon_s + \tau_t + \upsilon_s\, \boldsymbol{t} + \beta_2\, X_{1\ i,s,t} + \beta_3\, X_{2\ s,t} + \varepsilon_{i,s,t}$$

This study estimates the effect of state MML implementation on a variety of individual substance use behaviors. The substance use outcomes ($SubUse_{i,s,t}$) assessed in the main analysis include five outcomes related to marijuana use: (i) past-month marijuana use; (ii) past-month "almost daily or daily" use (i.e., more than 20 days of marijuana use); (iii) past-month frequency of marijuana use; (iv) past-year marijuana initiation; and (v) marijuana abuse/dependence according to DSM-IV diagnostic criteria. I also assessed eight outcomes related to the use of alcohol and other substances: (i) past-month total amount of drinks, (ii) past-month frequency of binge drinking (i.e., having five or more drinks on the same occasion on at least one day), (iii) alcohol abuse/dependence, (iv) past-month engagement in both marijuana use and binge drinking, (v) marijuana use while drinking, (vi) past-year non-medical use of prescription pain medication, (vii) past-year heroin use, and (viii) past-year cocaine use.

Two model specifications are estimated. The first model studies implementation of an MML as a whole, whereas the second model, by replaced a single dichotomous MML indicator ($MML_{s,t}$) with four indicators that represent key MML provisions, scrutinizes the potential policy heterogeneity between individual components of an MML. Specifically, the four key provisions assessed in the second model concern eligibility of "non-specific pain" ($Pain_{s,t}$), requirement of patient registry ($Registry_{s,t}$), permission for retail dispensary ($Dispensary_{s,t}$), and allowance for home cultivation ($Home_{s,t}$) (Pacula, et al., 2015; Pacula and Sevigny, 2014; Anderson and Rees, 2014).

Both models include state and year fixed effects (υ_s and τ_t) to account for the time-invariant state heterogeneity as well as the national secular trend and common shocks related to substance use. The models also include state-specific linear time trends ($\upsilon_s\, t$) to account for the unobserved state-level factors that evolve over time at a constant rate (e.g., social norms and public sentiments related to substance use). Additional covariates include individual-level measures of age, gender, race/ethnicity, self-reported health, household income, marital status, educational attainment, college enrollment, employment status, and urban residence ($X_{1\ i,s,t}$). Time-varying covariates at the state level are also included in the models, which are state-level measures of unemployment rate, average personal income, median household income, beer tax rate, and implementation of marijuana decriminalization/depenalization ($X_{2\ s,t}$). Standard errors are clustered at the state level (Bertrand, Duflo, and Mullainathan, 2004).

FIGURE 1.1 OVERARCHING CONCEPTUAL FRAMEWORK

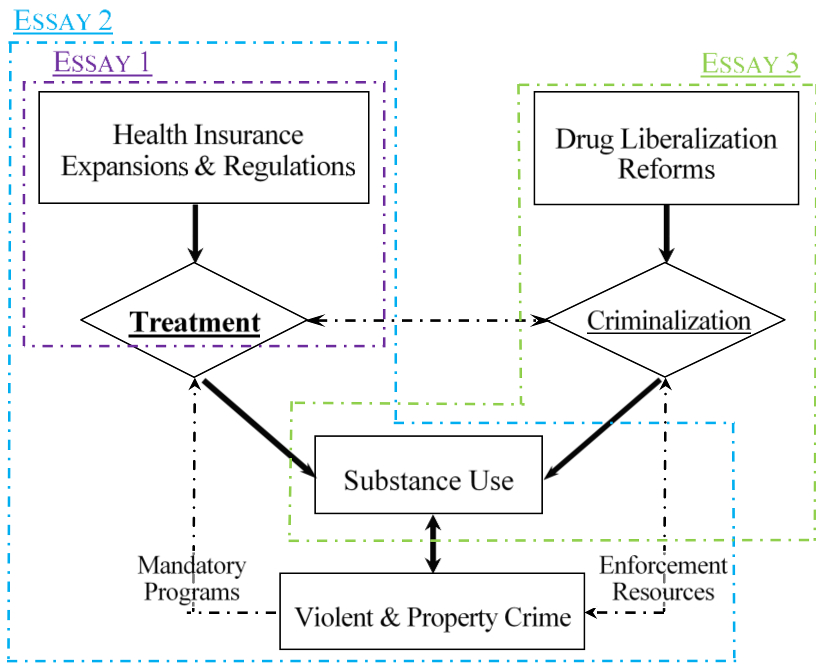


FIGURE 1.2 CONCEPTUAL FRAMEWORK OF ESSAY 1

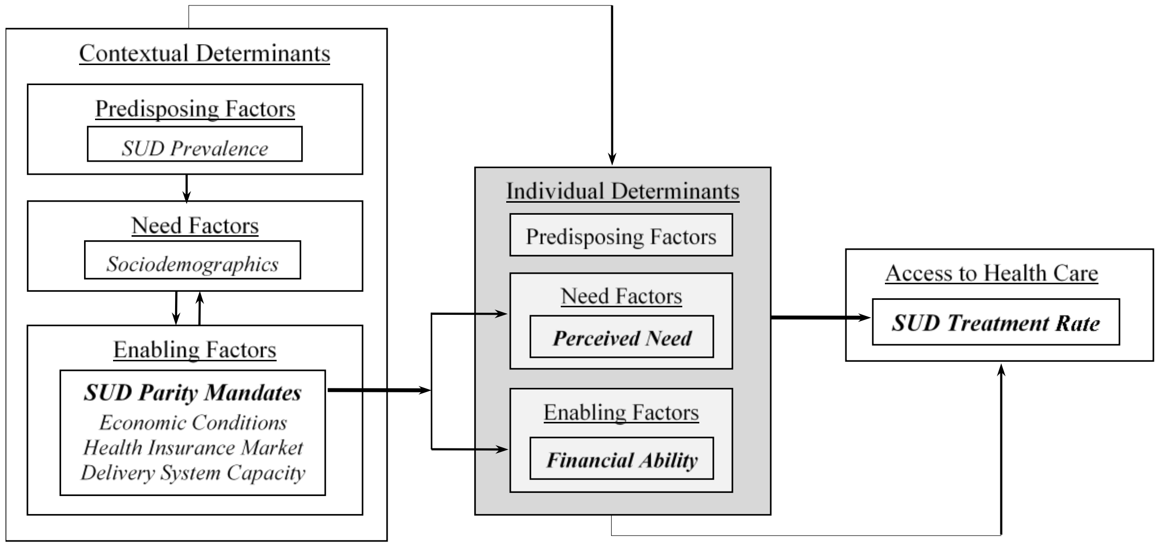


FIGURE 1.3 CONCEPTUAL FRAMEWORK OF ESSAY 2

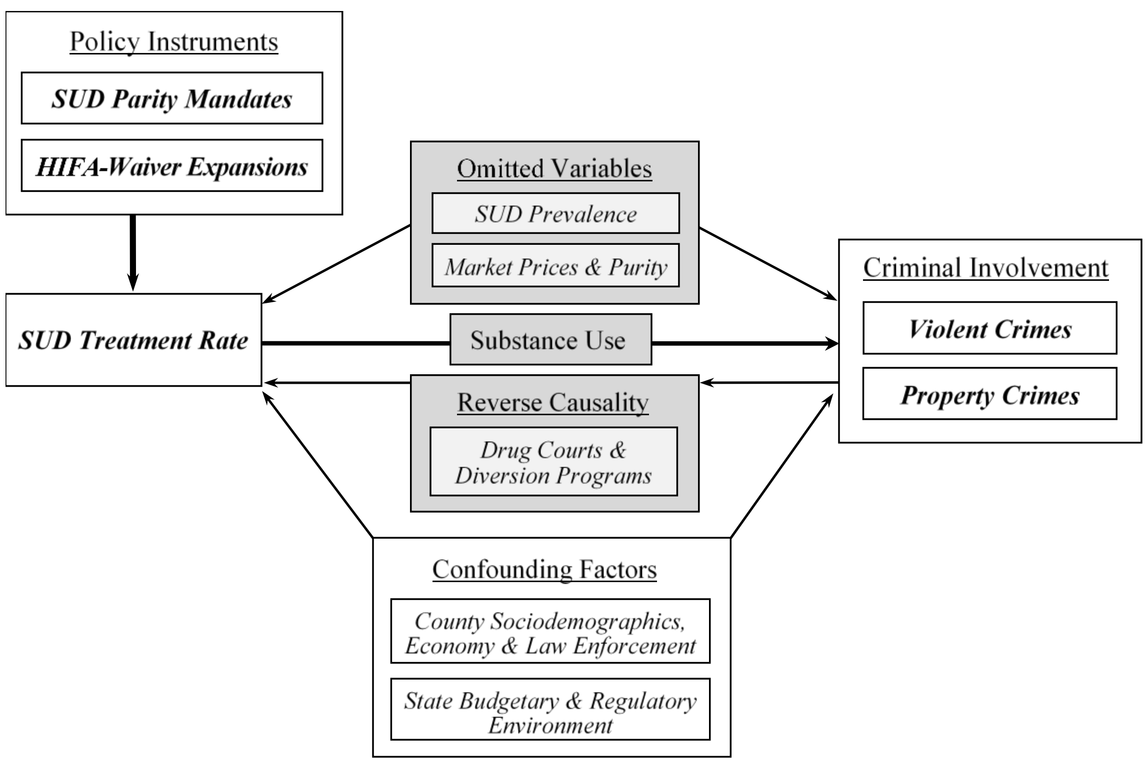
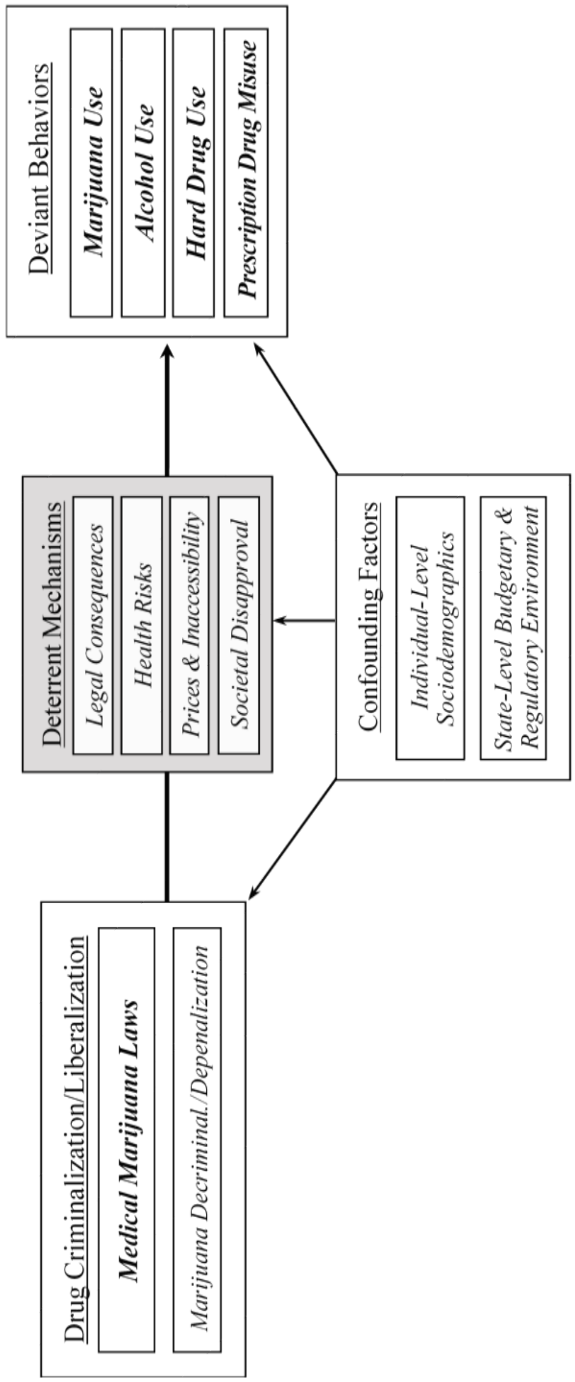


FIGURE 1.4 CONCEPTUAL FRAMEWORK OF ESSAY 3



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CHAPTER 2:

State Parity Laws and Access to Treatment for Substance Use Disorder in the United States: Implications for Federal Parity Legislation

IMPORTANCE: *The passage of the 2008 Mental Health Parity and Addiction Equity Act and the 2010 Affordable Care Act incorporated parity for substance use disorder (SUD) treatment into federal legislation. However, prior research provides us with scant evidence as to whether federal parity legislation will hold the potential for improving access to SUD treatment.*

OBJECTIVE: *To examine the effect of state-level SUD parity laws on state-aggregate SUD treatment rates and to shed light on the impact of the recent federal SUD parity legislation.*

DESIGN, SETTING, & PARTICIPANTS: *We conducted a quasi-experimental study using a two-way fixed-effect method. We included all known specialty SUD treatment facilities in the United States and examined treatment rates from October 1, 2000, through March 31, 2008. Our main source of data was the National Survey of Substance Abuse Treatment Services, which provides facility-level information on specialty SUD treatment.*

INTERVENTIONS: *State-level SUD parity laws during the study period.*

MAIN OUTCOMES & MEASURES: *State-aggregate SUD treatment rates in all specialty SUD treatment facilities and specialty SUD treatment facilities accepting private insurance.*

RESULTS: *The implementation of any SUD parity law increased the treatment rate by 9% ($p<0.001$) in all specialty SUD treatment facilities and by 15% ($p=0.02$) in facilities accepting private insurance. Full parity and parity only if SUD coverage is offered increased the SUD treatment rate by 13% ($p=0.02$) and 8% ($p=0.04$), respectively, in all facilities and by 21% ($p=0.03$) and 10% ($p=0.04$), respectively, in facilities accepting private insurance.*

CONCLUSION & RELEVANCE: *We found a positive effect of the implementation of state SUD parity legislation on access to specialty SUD treatment. The positive association is more pronounced in states with more comprehensive parity laws. Our findings suggest that federal parity legislation holds the potential to improve access to SUD treatment.*

* A published journal article of this study is available:
http://archpsyc.jamanetwork.com.proxy.library.emory.edu/article.aspx?articleid=1761269
Wen, Hefei, Janet R. Cummings, Jason M. Hockenberry, Laura M. Gaydos, and Benjamin G. Druss. 2013 "State parity laws and access to treatment for substance use disorder in the United States: implications for federal parity legislation." *JAMA Psychiatry*, 70(12): 1355-1362.

The authors declare that they have no relevant or material financial interests that relate to the research described in this study. The study was approved by the Emory University Institutional Review Board (IRB) through an expedited review procedure.

2.1 Introduction

An estimated 23 million Americans had a substance use disorder (SUD) in 2010, including abuse of or dependence on alcohol and/or illicit drugs (US Department of Health and Human Services, 2011). A growing body of literature has demonstrated the efficacy and cost-effectiveness of treatment for SUD. Specialty SUD treatment services such as outpatient psychosocial therapy and opioid maintenance therapy have proved to be effective in improving health (Winklbaur, et al., 2008; Roux, et al., 2008; Mojtabai and Zivin, 2003; Tanner-Smith, Wilson, and Lipsey, 2013; Greenfield, et al., 2007; Fiellin, et al., 2011; Dismuke, et al., 2004), reducing crime (Mojtabai and Zivin, 2003; Tanner-Smith, Wilson, and Lipsey, 2013; Greenfield, et al., 2007; Sindelar, et al., 2004; Zarkin, et al., 2010; McCollister and French, 2003), increasing employment (Dismuke, et al., 2004; Sindelar, et al., 2004; Hubbard, Craddock, and Anderson, 2003; Parran, et al., 2010; French, et al., 2002), and producing a wide range of social benefits (Tanner-Smith, Wilson, and Lipsey, 2013; Greenfield, et al., 2007; Sindelar, et al., 2004; Hubbard, Craddock, and Anderson, 2003; Parran, et al., 2010; French, et al., 2002). Nonetheless, only 17% of those individuals who needed SUD treatment received any treatment for their condition, and only 11% (2.6 million) received treatment in a specialty setting (SAMHSA, 2011).

Financial barriers in general and limited insurance coverage for SUD in particular pose a major barrier to access to specialty SUD treatment among those individuals perceiving a need for treatment (SAMHSA, 2011; Bouchery, et al., 2012). Ever since the inception of third-party payment for SUD treatment, coverage for SUD treatment has been more restrictive than that for medical/surgical treatment in terms of cost sharing and treatment limitations (Horgan and Merrick, 2001; Amaro, 1999; Sturm and Sherbourne, 2001). To address these discriminatory restrictions, more than one-half of the states in the United States have enacted SUD parity laws during the past two decades requiring employment-related group health plans to provide coverage for SUD treatment equal to that for comparable medical/surgical treatment (Robinson, et al., 2006).

More recently, the passage of the 2008 Mental Health Parity and Addiction Equity Act (MHPAEA) incorporated SUD parity into federal legislation for the first time (Busch, 2012). However, the MHPAEA mandates parity only for employment-related and self-funded group health plans and only for existing SUD coverage offered by those plans (i.e., parity-if-offered). Subsequently, provisions of the 2010 Affordable Care Act (ACA) extended SUD parity to Medicaid-managed care plans, Medicaid benchmark and benchmark-equivalent plans, and state health insurance exchange plans (Barry and Huskamp, 2011). Furthermore, the ACA requires that coverage for SUD treatment, as an essential health benefit, must be offered and must be offered on par with that for comparable medical/surgical treatment (i.e., full parity).

Nonetheless, prior research provides us with scant evidence about the likely effect of federal parity legislation on access to SUD treatment. Two studies examined SUD parity laws in the private insurance market of a particular state (i.e., Vermont and Oregon) (Rosenbach, et al., 2003; McConnell, Ridgely, and McCarty, 2012), and a third study evaluated SUD parity implementation in the Federal Employees Health Benefits program (Azzone, et al., 2012). None of these studies found a significant improvement in access to SUD treatment attributable to the implementation of SUD parity. However, findings from these studies may have limited generalizability to the anticipated effect of the recent federal SUD parity legislation. First, the study examining Vermont's 1998 parity law did not include a comparison group to control for the downward secular trend in access to SUD treatment nationwide (Rosenbach, et al., 2003). In addition, the study examining Oregon's 2007 parity law captured only a policy change from partial parity (implemented in 2000) to full parity (McConnell, Ridgely, and McCarty, 2012), which might be confounded by Oregon's simultaneous reform of methamphetamine regulation (effective in July 2006) that dramatically curbed the underlying prevalence rate (Dobkin and Nicosia, 2009). Finally, the study evaluating parity of the Federal Employees Health Benefits focused on a study population with a unique risk profile (e.g., less likely to use and abuse or to depend on substance) and financial capacity (e.g., less likely to have financial barriers to treatment) that may limit the generalizability of the results to broader populations with private insurance (Buck, et al., 1999).

The present study advances the existing literature by analyzing all state-level SUD parity laws in the private insurance market implemented from October 1, 2000, through March 31, 2008, and applying a rigorous quasi-experimental design to the variations among those state parity laws in the timing of the implementation and the comprehensiveness of the mandate. We hypothesized that: (i) the implementation of SUD parity legislation increased the SUD treatment rate at the state level; (ii) the increase in the treatment rate was more pronounced in states with more comprehensive SUD parity laws; and (iii) the increase in the SUD treatment rate associated with the implementation of SUD parity laws was concentrated in facilities accepting private insurance.

2.2 Methods

2.2.1 Data Sources

The main source of our data is the National Survey of Substance Abuse Treatment Services (N-SSATS) (OAS, 2009), which provides facility-level information on specialty SUD treatment from 2000 through 2008. In 2002, the reference date for the annual survey was changed from September to March to enhance the response rate, leaving a gap period from September 2000 to March 2001 with no data collected.

The N-SSATS facility data cover all known specialty SUD treatment facilities, allowing for a nearly complete enumeration of specialty SUD treatment services in the United States. A specialty SUD treatment facility, according to N-SSATS, is defined as a hospital, a residential SUD facility, an outpatient SUD treatment facility, a mental health facility with an SUD treatment program, or other facility with an SUD treatment program providing the following treatment services: (i) outpatient, inpatient, or residential/rehabilitation SUD treatment; (ii) detoxification treatment; (iii) opioid treatment programs such as maintenance therapy with methadone and levo-α-acetylmethadol; and (iv) halfway-house services that include SUD treatment. Throughout the study period, response rates ranged from 92% to 95% (OAS, 2009). We merged the N-SSATS data with select state-level measures from nationally representative data sets to provide supplementary information on important state socioeconomic characteristics and policy environment (discussed below).

2.2.2 Analytic Sample

We combined the N-SSATS data sets from 2000 to 2008 and converted the facility-level data to the state level to create an analytic panel of 392 state-year observations across the 49 states and 8 years. Virginia was excluded from the analysis because it was the only state that moved away from parity when full parity was repealed and regressed to partial parity in 2004.

2.2.3 Variable Measurement

Dependent Variable: All surveyed facilities were requested to report the total SUD treatment counts in the most recent 12 months before the survey. The N-SSATS method specified that the treatment count should only include the initial entry of a client into treatment; subsequent visits to the same service or transfer to a different service within a single continuous course of treatment were excluded. The missing-item rate for treatment count was approximately 7% during the study period.

The treatment counts in all specialty facilities were aggregated to each state *s* in each year *t* to determine the state-aggregate annual number of SUD treatment entries. We also aggregated the treatment counts only for facilities that accept private insurance. Both measures of the state-aggregate annual treatment entries were then weighted by the state population size to generate the 2 dependent variables assessing the following: (i) the treatment rate among all facilities ($Treatment\ Rate_{st}$) as the number of SUD treatment entries into all specialty SUD treatment facilities per 100 state residents in each state *s* for each year *t*; and (ii) the treatment rate for facilities accepting private insurance ($Treatment\ Rate\text{-}PI_{st}$) as the number of SUD treatment entries into specialty SUD treatment facilities that accept private insurance per 100 state residents in each state *s* for each year *t*.

Primary Independent Variables: In a broad sense, SUD parity refers to a policy mandating insurance coverage for SUD treatment to be “no more restrictive” than coverage for comparable medical/surgical treatment, with respect to cost sharing (e.g., deductibles, copayments, coinsurance, and out-of-pocket expenses), treatment limitations (e.g., annual or lifetime limits on number of visits or hospital days), or both (Hennessy and Goldman, 2001). The first independent variable of interest is a dichotomous indicator for the implementation of any parity law in a given state *s* during a given year *t* ($Parity_{st}$). The implementation indicator was assigned a value of 1 for each full year subsequent to the time when a state first implemented its SUD parity law and a value of 0 for the pre-implementation periods and for states without any SUD parity law.

We also created a categorical measure to distinguish among the following different levels of comprehensiveness in the implementation of parity: (i) full parity requires SUD coverage to be offered and offered on par with the comparable medical/surgical coverage in all aspects of cost sharing and treatment limitations; (ii) partial parity, though requiring that SUD coverage be offered, allows for discrepancies between SUD coverage and comparable medical/surgical coverage in some aspects of cost sharing and treatment limitation; (iii) parity-if-offered does not require SUD coverage to be offered, but if offered, it should be on par with the comparable medical/surgical coverage in all aspects of cost sharing and treatment limitations.

To assess the implementation and the comprehensiveness of the state SUD parity laws, we reviewed the relevant information provided by the Substance Abuse and Mental Health Services Administration (SAMHSA), the National Conference of State Legislatures, and other advocacy organizations. We also referred to the original state statutes to detect the subtlety in statutory language and to reconcile the inconsistencies among various sources. Table 2.1 presents detailed information on state SUD parity laws during the study period.

Covariates: To account for the state-year heterogeneity, we included key time-varying sociodemographic characteristics and policy environment factors that have been extensively documented to influence access to SUD treatment (Bouchery, et al., 2012; Cook and Alegría, 2011; Cummings, Wen, and Druss, 2011). Our covariates constituted the percentage of state population who are: (i) black or African American, (ii) Hispanic or Latino, (iii) living in poverty (i.e., at or below the federal poverty line), (iv) classified with SUD (i.e., meeting the DSM-IV diagnostic criteria for alcohol abuse/dependence and/or illicit drug abuse/dependence), and (v) eligible for Medicaid. We also included the per capita amount of the Substance Abuse Prevention and Treatment Block Grant (SAPTBG) allocated to the state as a proxy for system capacity (Buck, 2011). The SAPTBG represents a significant federal contribution to the state budgets for substance abuse prevention and treatment systems and accounts for approximately 40% of public funds expended by states for SUD treatment. In 2001, 16 states reported that more than half of their total funding for SUD treatment programs came from the SAPTBG.

In addition to the sociodemographic and policy covariates, we adjusted for the target population and exemption conditions that are commonly included in state SUD parity legislation. Most parity laws apply only to employment-related group health plans, leaving the individual (i.e., non-employment-based) health insurance market unregulated. Moreover, the federal preemption by the Employee Retirement Income Security Act (ERISA) of 1974 (Chirba-Martin and Brennan, 1994) does not allow state legislatures to impose health insurance regulations on self-insured business (usually large employers). Some states also exempt employers with fewer than 50 or fewer than 20 employees, further limiting the reach of SUD parity (Buchmueller, et al., 2007). When we considered the availability of the consistent data across the study states and years, we controlled for the percentage of the state population: (i) covered by employer-sponsored health insurance, (ii) covered by individually purchased health insurance, (iii) with large employers (i.e., > 500 employees), and (iv) with small employers (i.e., < 20 employees).

2.2.4 Statistical Analysis

We analyzed the effect of state SUD parity laws on state-aggregate SUD treatment rates, using two-way (i.e., state and year) fixed-effect modeling to account for unobserved or unmeasured factors in the treatment rates that are systematically correlated with the parity laws. The two-way fixed-effect approach can be viewed as an extension of the difference-in-difference framework to fit multiple-unit and multiple-time models that go beyond the traditional two groups (i.e., intervention vs. comparison) and two periods (i.e., before vs. after) (Wooldridge, 2001). By distinguishing the real impact of parity legislation from the confounding factors of the state heterogeneity (Sturm and Pacula, 1999) and the national secular trend, we are able to obtain unbiased estimates of the effect of state SUD parity laws.

We estimated four models. Model 1 estimated the SUD treatment rate among all specialty SUD treatment facilities at state *s* in year *t* ($Treatment\ Rate_{st}$) as a function of the dichotomous indicator of SUD parity implementation ($Parity_{st}$), the state fixed effect (υ_s), the year fixed effect (τ_t), the state sociodemographic and policy covariates ($Covariate\ Vector_{st}$), and an idiosyncratic error term (ε_{st}). Model 2 replaced the dichotomous indicator of any SUD parity implementation ($Parity_{st}$) with the categorical variable of the comprehensiveness in parity mandate ($Full\ Parity_{st}$, $Partial\ Parity_{st}$ and $Parity\text{-}If\text{-}Offered_{st}$). The dependent variable of both models, the SUD treatment rate among all specialty SUD treatment facilities ($Treatment\ Rate_{st}$), was measured based on the entire population instead of those targeted by state parity. The estimated effect of parity legislation, in this sense, would be diluted over a mixture of target (i.e., those groups with private insurance plans affected by parity) and nontarget groups (i.e., those groups with no insurance, with public insurance, or with private insurance plans not affected by parity). To refine our crude estimates, we also limited the treatment rate measure to facilities accepting private insurance ($Treatment\ Rate\text{-}PI_{st}$) and re-estimated the two models described above.

All estimated standard errors were clustered at the state level to correct for the serial correlation that otherwise leads to false rejections of the null hypothesis (Bertrand, Duflo, and Mullainathan, 2004).

2.3 Results

The Figure 2.1 shows an upward trend in the SUD treatment rate in parallel with the implementation of SUD parity legislation. Among the 10 states that first implemented SUD parity or extended their parity laws to a higher level of comprehensiveness from 2000 through 2008, the mean SUD treatment rate rose from 1.38 percentage points (per 100 population) during the year immediately before the parity implementation to 1.53 percentage points in the year immediately after implementation. The pre-parity and post-parity change in the SUD treatment rate was equivalent to an 11% increase (11% = $[1.53 - 1.38] \div \{[1.53 + 1.38] \div 2\}$). Among states that did not change their SUD parity status, the mean SUD treatment rate fell from 1.44 to 1.38 percentage points during the same period, which corresponds to an decrease of 4% (4% = $[1.38 - 1.44] \div \{[1.38 + 1.44] \div 2\}$). This observational trend comparison demonstrated a positive association between SUD parity and treatment rate.

Table 2.2 summarizes the descriptive statistics for the following three groups of states: (i) the 10 parity states that first implemented parity laws or extended their laws from 2000 through 2008; (ii) the 23 states that do not have SUD parity; and (iii) the other 16 states that first implemented parity laws before 2000 and did not change their laws during the study period. We combined groups 2 and 3 as the control group representing the states without changes in parity laws during the study period. The two-sample t-tests of mean differences between the 10 parity states with changes in their parity laws and the remaining states without changes indicated that the parity states had a significantly higher rate of SUD treatment in all specialty SUD treatment facilities ($p = 0.03$) and in facilities accepting private insurance ($p < 0.001$).

Table 2.3 reports the regression results for the estimated effect of SUD parity implementation on the SUD treatment rate. The implementation of any SUD parity law significantly increased the treatment rate in all specialty SUD treatment facilities (Model 1.1: marginal effect [ME] = 0.13 percentage points [95% CI: 0.04-0.23]) and in facilities accepting private insurance (Model 2.1: 0.16 [0.03-0.30]). To place the magnitude of effect into context, we translate the estimated ME (i.e., change in percentage points per 100 state residents) into the percentage of change in the SUD treatment rate. Given that the mean SUD treatment rate was 1.40 percentage points in all specialty SUD treatment facilities and 1.10 percentage points in facilities accepting private insurance, changes of 0.13 and 0.16 percentage points, respectively, can be translated into a 9% increase in the overall SUD treatment rate (i.e., 9% = 0.13 ÷ 1.40), and a 15% increase in the SUD treatment rate for facilities accepting private insurance (i.e., 15% = 0.16 ÷ 1.10).

When considering the comprehensiveness of the parity legislation (Table 2.3), full parity and parity-if-offered increased the SUD treatment rate by 13% (Model 1.2: ME = 0.18 percentage points [95% CI: 0.03-0.33]) and 8% (Model 1.2: 0.12 [0.00-0.23]), respectively, in all facilities and by 21% (Model 2.2: 0.23 [0.03-0.43]) and 10% (Model 2.2: 0.11 [0.00-0.22]), respectively, in those accepting private insurance. The influence of partial parity on the treatment rate was not statistically significant across models.

2.4 Discussion

Our findings indicate that the implementation of state SUD parity legislation results in a significant improvement in access to specialty SUD treatment. The implementation of any SUD parity law increased the treatment rate by 9% in all specialty SUD treatment facilities and by 15% in facilities accepting private insurance. Our study contributes to the existing literature by using state-level panel data on a nearly complete enumeration of all treatment counts in specialty SUD treatment facilities, harnessing all legislative changes in state-level SUD parity laws during the study period, and tailoring a rigorous quasi-experimental design to this series of state experiments.

Our study also advances the literature by documenting the extent to which the comprehensiveness of SUD parity matters. The implementation of full parity laws led to the largest increases in SUD treatment rate (a 13% increase), followed by parity-if-offered laws (an 8% increase). The effect of partial parity, on the other hand, was not statistically significant ($p = .12$).

When considering the implications of our findings for the anticipated impact of recent federal SUD parity legislation, the MHPAEA (i.e., parity-if-offered) can be expected to have a modest effect on access to SUD treatment. The MHPAEA not only regulates quantitative limits (e.g., annual or lifetime limits on the number of visits or hospital days) addressed by previous state-level parity laws but also mandates parity for a wider range of non-quantitative restrictions such as medical necessity, prior authorization, or utilization review (McConnell, Ridgely, and McCarty, 2012; McConnell, et al., 2012; Goldman, McCulloch, and Sturm, 1998; Ma and McGuire, 1998). Given the dominance of these managed care mechanisms in the SUD service arrangements of private health plans, the inclusion of the non-quantitative managed care restrictions into the MHPAEA may enable this legislation to yield larger effects on the SUD treatment rate than we estimated for the state-level parity-if-offered laws.

Under the ACA, the full-parity provision, coupled with insurance expansion, is likely to further improve the access to SUD treatment beyond the impact of state-level full-parity laws. The ACA will expand health insurance to approximately 50 million uninsured persons; SUD coverage gained by the newly insured persons through Medicaid benchmark or benchmark-equivalent plans or state health insurance exchange plans will be subject to full parity (Barry and Huskamp, 2011). In our analysis of the state parity regulations in the employment-related group insurance market, the increases associated with full SUD parity were confined to facilities accepting private insurance. By expanding the scope of parity to public insurance programs, the ACA will reach a much larger population and may lead to an unparalleled growth of the SUD treatment rate in the public and private sectors.

The estimated growth in SUD treatment rate will only be possible if the capacity of the SUD treatment system suffices to absorb new entrants into the system. At present, most SUD treatment is provided in the specialty treatment sector, and researchers have already raised concerns that SUD specialty treatment programs may face challenges in meeting potential needs (Buck, 2011). The Prevention and Public Health Fund created under the ACA offers grant support to develop more comprehensive SUD screening, brief intervention, referral, and treatment programs, which will enhance the capacity of primary care sites to provide SUD care. Enhanced funding for federally qualified health care centers and Medicaid health home initiatives may also help to fill the capacity gap. Nonetheless, as the MHPAEA and ACA unfold, tracking the effect of both laws on SUD treatment to ensure that they are able to fulfill their promise in improving access to SUD treatment will be critical.

The conclusions of this study should be interpreted in light of the following limitations. First, we cannot identify individuals' insurance coverage and their employment status in the facility-level N-SSATS data or find more detailed facility-level information on the percentage of treatment entries/clients who were covered by the health insurance plans subject to parity. Thus, the dependent variable, the state-aggregate SUD treatment rate, was measured based on the entire population instead of the population targeted by state parity laws. We refined our analysis by restricting the measurement of the treatment rate to facilities accepting private insurance, which yielded a larger point estimate of the parity effect. We also conducted sensitivity analyses for facilities not accepting private insurance and found no difference in SUD treatment rates attributable to parity. Considered together, these additional analyses suggest that the effect of SUD parity on the treatment rate is primarily driven by the increased treatment rate among the target population. Second, N-SSATS did not ask facilities to report treatment counts for alcohol and illicit drug use separately; thus, we were only able to assess the effect of parity on combined SUD treatment rates, despite their distinct legal status, patterns of treatment, and consequently individuals' policy sensitivity and price elasticity. Third, as with any observational study, we cannot definitively establish causality between the implementation of SUD parity laws and access to SUD treatment. However, the rigorous methods and robust results strongly suggest that parity improved access.

Despite these limitations, our study provides useful insight into the potential effect of the implementation and the comprehensiveness of SUD parity on access to SUD treatment and, in broad terms, the potential of financial incentives and policy leverage to influence treatment-seeking behavior. We found that the implementation of state SUD parity laws significantly increased the SUD treatment rate and that the increase was more pronounced in states implementing more comprehensive laws. These findings suggest that the MHPAEA of 2008 and the ACA of 2010 hold the potential to improve access to SUD treatment.

TABLE 1.1 SUMMARY OF STATE-LEVEL SUBSTANCE USE DISORDER (SUD) PARITY LAWS, 2000-2008

Parity status between 2000 and 2008		**State** (Effective year of parity)							
	States first implementing or improving parity laws during 2000-2008								
Any Change	No Parity→ Parity-If-Offered	**KY** (2001)		**WI** (2004)					
	No Parity → Partial Parity	**MI** (2001)		**MT** (2002)		**NH** (2003)			
	No Parity → Full Parity	**DE** (2001)		**WV** (2004)					
	Partial Parity → Full Parity	**RI** (2002)		**ME** (2003)		**OR** (2007)			
	States with parity laws existing before 2000 with no further changes (always parity)								
	Parity-If-Offered	AR	LA	MN	MO	TN			
	Partial Parity	AK	HI	KS	NV	ND	PA	TX	WA
	Full Parity	CT	MD	VT					
No Change	***States with no mandate or weak laws (no parity)***								
	Parity-Like Mandate+	IN	MA						
	Weak Mandate†	FL	GA	NC‡	NY	SC‡	UT		
	Weak† & Alcohol Only	AL	CA	CO	IL	MS	NE	NM	SD
	No Mandate	AZ	ID	IA	NJ‡	OH‡	OK	WY	

Note:

\+ Parity-like mandate:
MA (2001): Full parity for SUD treatment only if co-occurring with a mental illness;
IN (2003): Parity-if-offered for SUD treatment only if required in the treatment of a mental illness;

† Weak mandate ("partial-parity-if-offered") doesn't require SUD coverage to be offered, and only requires the offered coverage to be on a par with the comparable medical/surgical coverage in limited aspects of cost sharing or treatment limitations, which is not considered to be parity;

‡ Parity ONLY for state employee plans: OH (1990/1995), NC (1997), NJ (2000), SC (2002).

TABLE 2.2 DESCRIPTIVE STATISTICS FOR STATES WITH CHANGES IN SUD PARITY STATUS, VS. STATES WITH NO CHANGE IN PARITY STATUS, 2000-2008

	Change in Parity		**No Change in Parity**						**Mean-Diff†**
			Always Parity		No Parity		No Change Total		
	Mean	*(Sd.)*	*Mean*	*(Sd.)*	*Mean*	*(Sd.)*	*Mean*	*(Sd.)*	*p-value*
# States-Year Observations	80=10×8		128=16×8		184=23×8		312=39×8		--
<u>Dependent Variable</u>									
% SUD Treatment Rate in All Facilities	1.5	(0.4)	1.3	(0.5)	1.4	(0.5)	1.4	(0.5)	**0.03**
% SUD Treatment Rate in Facilities Accepting Private Insurance	1.3	(0.4)	1.0	(0.5)	1.1	(0.5)	1.1	(0.5)	**<0.001**
% Facilities Accepting Private Insurance	80.3	(9.5)	70.8	(7.7)	64.2	(6.8)	66.2	(7.2)	**<0.001**
<u>Covariates</u>									
% African/Black	6.1	(6.2)	10.4	(9.2)	11.7	(10.6)	11.2	(10.0)	**<0.001**
% Hispanic/Latino	4.1	(3.2)	9.1	(9.8)	10.5	(10.3)	9.9	(10.1)	**<0.001**
% Poverty	11.9	(3.0)	11.9	(3.2)	12.4	(2.9)	12.2	(3.0)	0.43
% SUD Prevalence	9.6	(1.2)	9.4	(0.9)	9.3	(1.1)	9.3	(1.0)	**0.03**
% Medicaid-Eligible	13.4	(3.7)	12.6	(3.5)	12.9	(3.4)	12.8	(3.4)	0.12
$ SAPTBG Funding (per capita)	5.6	(1.1)	5.5	(1.1)	5.4	(0.8)	5.4	(0.9)	0.24
% Employer-Sponsored Private-Insured	62.2	(6.0)	60.7	(6.2)	59.8	(5.6)	60.1	(5.8)	**0.005**
% Individual-Purchased Private-Insured	9.5	(2.8)	10.1	(2.9)	9.8	(2.9)	9.9	(2.9)	0.25
% Workforce in 500+ Employers	44.6	(6.4)	48.0	(5.5)	47.8	(5.5)	47.9	(5.5)	**<0.001**
% Workforce in 20- Employers	21.2	(4.3)	18.7	(2.8)	19.8	(3.4)	19.3	(3.2)	**<0.001**
# Population (1,000,000)	3.0	(2.8)	5.4	(5.2)	7.2	(7.8)	6.5	(6.9)	**<0.001**

Note:
† *p-value* for mean-difference is calculated based on two-sample t-test between 10 states with changes in parity (Column 1) and 39 states with no change (Column 4).

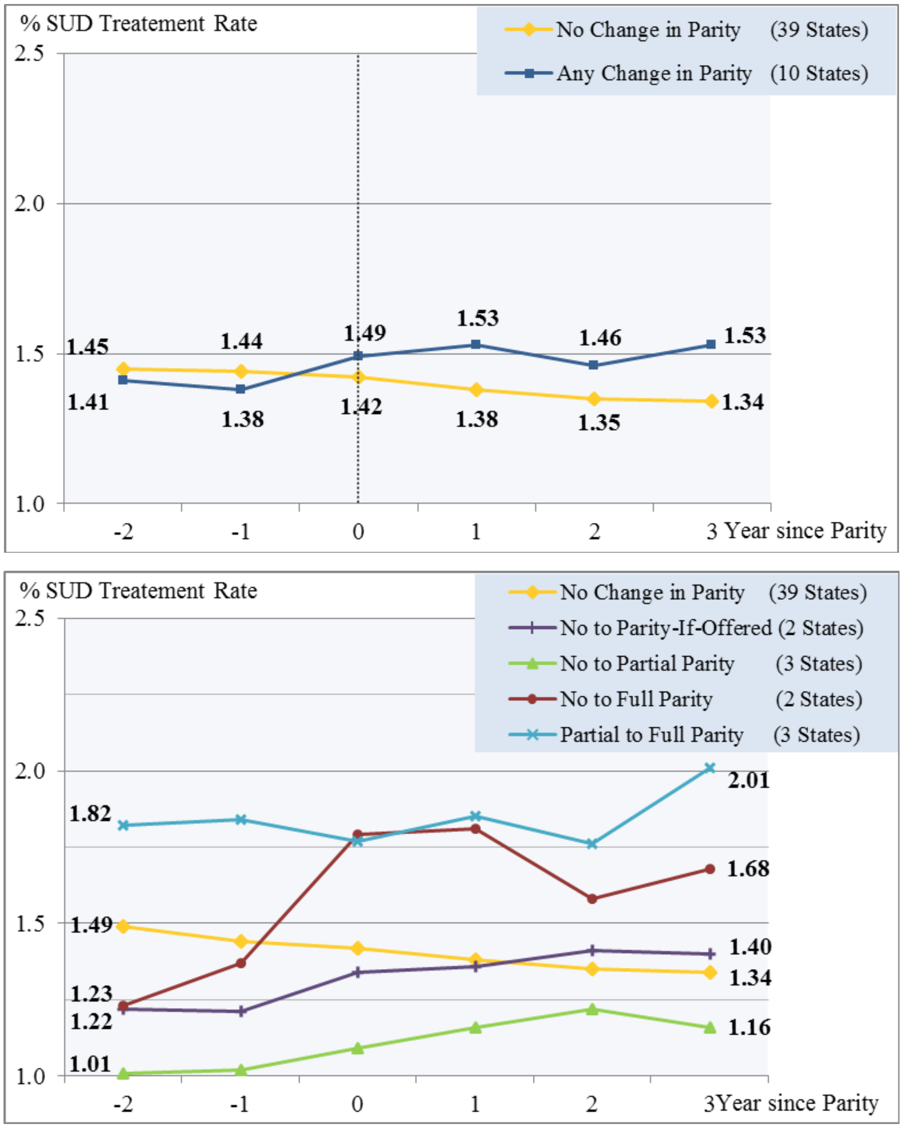
TABLE 2.3 ESTIMATED EFFECTS OF SUD PARITY IMPLEMENTATION AND OTHER COVARIATES ON THE SUD TREATMENT RATE

% SUD Treatment Rate	**All Facilities**			
	Model 1.1		Model 1.2	
	∂y/∂x (95% CI)		*∂y/∂x (95% CI)*	
Primary Independent Variables				
Parity	**0.13****	**(0.04, 0.23)**		
Full Parity			**0.18***	**(0.03, 0.33)**
Partial Parity			0.08	(-0.02, 0.19)
Parity-If-Offered			**0.12***	**(0.00, 0.23)**
Covariates				
% African/Black	-0.06	(-0.16, 0.03)	-0.07	(-0.16, 0.03)
% Hispanic/Latino	**-0.10***	**(-0.18,-0.02)**	**-0.10***	**(-0.18,-0.02)**
% Poverty	-0.03	(-0.08, 0.02)	-0.03	(-0.09, 0.02)
% SUD Prevalence	0.02	(-0.05, 0.08)	0.01	(-0.05, 0.08)
% Medicaid-Eligible	**0.02***	**(0.00, 0.04)**	**0.02***	**(0.00, 0.04)**
$ SAPTBG Funding per capita	-0.13	(-0.43, 0.17)	-0.13	(-0.43, 0.17)
% Employer-Sponsored Private-Insured	-0.01	(-0.03, 0.01)	-0.01	(-0.03, 0.01)
% Individual-Purchased Private-Insured	0.01	(-0.01, 0.03)	0.01	(-0.01, 0.03)
% Workforce in 500+ Employers	-0.01	(-0.08, 0.07)	-0.01	(-0.08, 0.07)
% Workforce in 20- Employers	-0.06	(-0.19, 0.07)	-0.06	(-0.20, 0.07)
R^2	0.88		0.89	

% SUD Treatment Rate	**Facilities Accepting Private Insurance**			
	Model 2.1		Model 2.2	
	∂y/∂x (95% CI)		*∂y/∂x (95% CI)*	
Primary Independent Variables				
Parity	**0.16***	**(0.03, 0.30)**		
Full Parity			**0.23***	**(0.03, 0.43)**
Partial Parity			0.10	(-0.02, 0.21)
Parity-If-Offered			**0.11***	**(0.00, 0.22)**
Covariates				
% African/Black	-0.04	(-0.15, 0.06)	-0.04	(-0.15, 0.06)
% Hispanic/Latino	**-0.07***	**(-0.14,-0.00)**	**-0.07***	**(-0.14, 0.00)**
% Poverty	**-0.05***	**(-0.09,-0.00)**	**-0.05***	**(-0.09,-0.00)**
% SUD Prevalence	-0.01	(-0.07, 0.05)	-0.01	(-0.07, 0.04)
% Medicaid-Eligible	0.01	(-0.01, 0.03)	0.01	(-0.01, 0.03)
$ SAPTBG Funding per capita	-0.10	(-0.35, 0.15)	-0.10	(-0.35, 0.15)
% Employer-Sponsored Private-Insured	-0.01	(-0.02, 0.01)	-0.01	(-0.02, 0.01)
% Individual-Purchased Private-Insured	-0.001	(-0.02, 0.02)	0.001	(-0.02, 0.02)
% Workforce in 500+ Employers	0.01	(-0.07, 0.08)	0.01	(-0.07, 0.08)
% Workforce in 20- Employers	-0.04	(-0.17, 0.09)	-0.04	(-0.17, 0.09)
R^2	0.88		0.89	

Note:
95% confidence intervals (CIs) in parentheses are calculated based on state-clustered standard errors; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Figure 1.1 Trends in SUD Treatment Rate by SUD Parity Status



Note:

Figure 2.1 presents state-aggregate SUD treatment rate during the pre- and post-parity period. We centered the year each parity state started to implement the law at Time 0. The vertical line represents the year during which each parity state started to implement or extend the law, and it corresponds to the period covered in: N-SSATS 2002 (April, 2001 to March, 2002) for DE and MI, N-SSATS 2003 (April, 2002 to March, 2003) for MT and RI, N-SSATS 2004 (April, 2003 to March, 2004) for ME and NH, N-SSATS 2005 (April, 2004 to March, 2005) for WI and WV, and N-SSATS 2007 (April, 2006 to March, 2007) 2007 for OR. Note that KY implemented parity during the gap year between N-SSATS 2000 and N-SSATS 2002, so Time 0 consisted of nine data points instead of ten. For the other "no change in parity" states, the treatment rates during 2002, 2003, 2004, 2005 and 2007 were weighted by 2/9, 2/9, 2/9, 2/9, and 1/9 to match the proportions of the states that implemented parity in a given year. Following the same procedure we determined Time -2, -1, 1, 2, and 3 for parity states, and then transferred "no change in parity" states to the corresponding time in accord with the parity states. Note that only 7 parity states were included for Time -1 (No data for KY, DE and MI), time 2 (No data for OR), and time 3 (No data for OR).

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CHAPTER 3:
The Effect of Substance Use Disorder Treatment Use on Crime: Evidence from Public Insurance Expansions & Health Insurance Parity Mandates

Substance use figures prominently in criminal behavior. As such increasing access to substance use disorder (SUD) treatment can potentially reduce crime. However, financial barriers often prevent people with SUD from receiving the treatment they need. We exploit the exogenous variation in the SUD treatment rate arising from insurance expansions under the Health Insurance Flexibility and Accountability waivers and the SUD parity mandates to identify the crime-reduction effect. We find that increased SUD treatment rate reduces rates of robbery, aggravated assault and larceny theft. The benefit-cost ratio estimates of expanded treatment on reducing crime range from 1.6 to 3.0.

(JEL I11, I13, K14, K42)

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"Punishment is the last and the least effective instrument in the hands of the legislator for the prevention of crime." *~ John Ruskin (1819-1900)*

3.1 Introduction

Substance use and crime are two of the most intractable social ills facing the United States, and they are inextricably linked. A positive correlation between substance use and crime has been observed in arrestee drug test results and inmate drug reports. Among arrestees who were booked on violent or property crimes, one in every four tested positive for illicit drug use at the time of arrest (ONDCP 2012). Moreover, among prison inmates charged with violent crimes, 52 percent reported being under the influence of alcohol or drugs when committing the crime, or committing the crime to acquire money to purchase drugs; among those charged with property crimes, this number is 39 percent (Miller, Levy et al. 2006).

To the extent that this observed correlation involves causality running from substance use to crime, interventions to reduce substance use should also reduce crime. Nonetheless, empirical evidence suggests that punitive approaches to substance control such as prohibition and the "war on drugs" have not led to significant crime reduction (Miron 1999; Kuziemko and Levitt 2004; Markowitz 2005)[4].

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[4] Miron (1999) used a century-long time-series trend of the U.S. national homicide rate from 1900 to 1995, and demonstrated that alcohol and drug prohibition was positively associated with homicide rate and accounted for half of the variation in the homicide rate. The author further proposed a "violence-as-dispute-resolution" hypothesis that prohibition enforcement encouraged the substitution of violent for nonviolent dispute resolution in illegal markets. Kuziemko and Levitt (2001) used state-level crime data between 1980 and 2000, and demonstrated that a 15-fold increase in drug-offense incarceration during the study period reduced total crime rate by no more than 3%. A back-of-the

In this paper we explore an area that has garnered relatively little attention in the economic literature on crime reduction, namely treatment for substance use disorder (SUD). We examine the effect of increasing the local SUD treatment rate on reducing violent and property crime rates based on county-level panels of SUD treatment and crime data between 2001 and 2008 across the United States. A major empirical concern in examining this relationship is that the local SUD treatment rate is potentially endogenous to crime rates. To address this concern we exploit the exogenous variation in the local SUD treatment rate induced by two state-level policies which expanded health insurance coverage for those with SUD. These two policies are the Health Insurance Flexibility and Accountability (HIFA) waivers (CMS 2001) and parity mandates for SUD treatment (SAMHSA 2006). The IV estimates reveal that an increase in the SUD treatment rate leads to an economically meaningful reduction in the rates of specific types of crimes (i.e., robbery, aggravated assault and larceny theft) for which theory suggests an increase in the SUD treatment rate should have an effect.

This study has implications for both public safety policy and health policy. Previous studies of the economic benefits of SUD treatment have often emphasized the direct health returns on treatment through recovery from addiction and the related productivity gains (Belenko et al. 2005). We instead focus on the public finance aspects of SUD treatment and

envelope estimate suggested that locking up drug offenders crowded out the criminals with higher marginal risks of recidivism, therefore investment in drug-offense incarceration was unlikely cost-effective. Markowitz (2005) used individual-level victimization surveys in the early 1990s, and demonstrated that higher beer taxes and higher cocaine prices only slightly lowered the probability of assault and robbery victimizations. These findings raised questions on the "war on drugs" into which limited resources were diverted away from other crime prevention programs.

crime reduction. Our estimates demonstrate a benefit-cost ratio of 1.6 to 3.0, that is, a 10 percent relative increase in the SUD treatment rate at an average cost of $1.6 billion yields a crime reduction benefit of $2.5 billion to $4.8 billion. This downstream benefit to public safety represents a sizable fraction of returns on SUD treatment. Specifically, as the U.S. criminal justice system scales back mandatory minimum sentences for low-level drug and other minor offenders who may also be substance users, replacing incarceration with better access to SUD treatment can be a cost-effective investment in public safety.

Furthermore, the first stage of our IV estimation is of interest in its own right. It provides previously undocumented evidence of a significant increase in the SUD treatment rate arising from public insurance expansions. This has direct relevance to the current health care reform discussions surrounding insurance expansion and "mainstreaming" of SUD treatment[5]. The Affordable Care Act (ACA) is expected to substantially expand insurance coverage. Much of this expansion will occur through Medicaid and in the health insurance exchanges, and will include coverage for those with SUDs who are also in the age groups more likely to commit these crimes. Because many SUD treatment services are classified as an "Essential Health Benefit", they must be offered by plans in the health insurance exchanges and offered at parity with medical/surgical benefits. In addition, those

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[5] SUD treatment has been predominantly provided in a separate specialty setting and operated as an independent part of the overall health care system. Under the current health care reform, incentives to create better integrated, person-centered health care hold the potential for integrating SUD treatment into the mainstream behavioral and general health care systems. Community mental health centers (CMHCs), which already provide some specialty SUD treatment, may be motivated by financial incentives to provide more comprehensive community-based SUD treatment. Non-specialty providers, such as health centers with the focus on primary care delivery, are also uniquely positioned to respond to the increased demand for SUD treatment arising from insurance expansion and parity legislation, and thereby become another major source of integrated care (Buck 2011).

with SUDs are recognized as a “medically frail” population for which a broad range of evidence-based treatment services should be available and fully covered under Medicaid (Beronio, Glied, and Frank 2014)[6]. We show that previous policies that expanded insurance coverage and benefits people with SUDs increases their treatment use, *and* that doing so led to a cost-effective public health approach to crime reduction.

3.2 Background

3.2.1 Theories of Substance Use, SUD Treatment and Crime

Contemporary criminological theories suggest that substance use is one of the root causes of crime. The most cited criminological theory on this causal relationship is Goldstein’s (2003) tripartite model, in which three hypotheses are provided to explain how substance use causes violent and property crimes. First, the pharmacological hypothesis states that violence may occur as a direct result of the intoxication. Intoxication of certain substances may trigger aggression and lead to violent offenses, or alternatively inhibit vigilance and result in victimization. Second, the economic motivation hypothesis states that substance users and addicts commit income-generating crimes to finance their

[6] Although it is expected that demand for SUD treatment would increase as a result of insurance expansions under the ACA, the current system’s capacity to supply SUD treatment may not suffice to meet the increased demand. Some supply-side barriers, for instance, are workforce shortage with declining number of training programs and graduates, lack of infrastructure and resources distributed to minority communities and rural areas, the reluctance of providers to accept Medicaid and other insurance for which the reimbursement rate is relatively low, and the challenge with the federal-state-local partnership in financing and delivery SUD treatment (Mechanic 2014; Cummings et al. 2014; Bishop et al. 2014). Therefore, expanding supply-side capacity may also be necessary and critical for the increased demand for SUD treatment arising from the ACA expansions to be fully realized. However, this is outside the purview of this study.

substance use habits. Economic motivation is particularly pronounced among young people and those with low income from legal activities. The third hypothesis, the institutional hypothesis, states that being involved in an illegal drug market can expose one to an increased risk of criminal offense and victimization: crime may arise when a drug buyer robs a dealer of the drugs, when a drug dealer collects debts, and when rival drug gangs dispute over territories or compete for monopolistic power (Goldstein 2003).

A systematic review of three-decade long literature concludes that, for all three hypotheses Goldstein proposed, empirical support exists, yet causal interpretations are difficult to make (Bennett, Holloway et al. 2008). Unobserved third factors, whether they be personal, situational, or environmental (e.g., low self-control, early-life trauma, social inequality, as well as poverty and other forms of social deprivation), may be the underlying causes of both substance use and crime. Nonetheless, to the extent that substance use is on the causal pathway to crime, SUD treatment should have the potential not only to reduce substance use but also to reduce crime.

Though motivated by the intuition of Goldstein's tripartite model, our theoretical framework draws more directly upon Becker's rational choice model of crime (Becker 1968). Based on Becker's model, we specify the following structural relationship between substance use and crime:

$$\boldsymbol{Crime_{i,j,t}} = f(\boldsymbol{Substance\ Use_{i,j,t}}, \boldsymbol{Substance\ Use_{i',j,t}}, Law\ Enforcement_{j,t}, X_{1\ i,,j,t}, X_{2\ i',,j,t}, Z_{1\ j,t})$$

(1)

In the structural equation, criminal offense or victimization is a function of the substance use by the potential perpetrator $Substance\ Use_{i,j,t}$, the substance use by the potential victim $\textit{Substance Use}_{i',j,t}$, the law enforcement resources $\textit{Law Enforcement}_{j,t}$, the other observed and unobserved individual factors associated with the propensity for criminal offense $X_{1\ i,,j,t}$ and the propensity for criminal victimization $X_{2\ i',,j,t}$, as well as the observed and unobserved contextual factors $Z_{1\ j,t}$ that help create or limit opportunities for crime.

Instead of estimating a structural relationship between substance use and crime, this paper estimates a reduced-form relationship between SUD treatment and crime. We derive the reduced-form equation by expressing the original terms of the substance use by the perpetrator and the victim as a function relating their substance use to SUD treatment:

$$\textbf{\textit{Substance Use}}_{\boldsymbol{i,j,t}} = f(\textbf{\textit{SUD Treatment}}_{\boldsymbol{i,j,t}}, \textit{Law Enforcement}_{j,t}, X_{3\ i,,j,t}, Z_{2\ j,t}) \quad (2)$$

$$\textbf{\textit{Substance Use}}_{\boldsymbol{i',j,t}} = f(\textbf{\textit{SUD Treatment}}_{\boldsymbol{i',j,t}}, \textit{Law Enforcement}_{j,t}, X_{4\ i',,j,t}, Z_{2\ j,t}) \quad (3)$$

where substance use by the potential perpetrator $\textit{Substance Use}_{i,j,t}$ and by the potential victim $\textit{Substance Use}_{i',j,t}$ is a function of SUD treatment use $\textit{SUD Treatment}_{j,t}$, the law enforcement resources $\textit{Law Enforcement}_{j,t}$, the other observed and unobserved individual factors of the perpetrator and the victim $X_{3\ i,,j,t}$ and $X_{4\ i',,j,t}$ that are associated with the propensity for substance use, as well as the observed and unobserved contextual factors $Z_{2\ j,t}$ that help create or limit the opportunities for substance use.

Substituting Equations (2) and (3) into the structural equation of crime Equation (1), we obtain the following reduced-form equation:

$$\textbf{\textit{Crime}}_{\boldsymbol{i,j,t}} = f(\textbf{\textit{SUD Treatment}}_{\boldsymbol{i,j,t}}, \textbf{\textit{SUD Treatment}}_{\boldsymbol{i',j,t}}, \textit{Law Enforcement}_{j,t}, X_{1\ i,,j,t}, X_{2\ i',,j,t}, X_{3\ i,,j,t}, X_{4\ i',,j,t}, Z_{1\ j,t}, Z_{2\ j,t}) \quad (4)$$

There is limited availability of individual person-level representative data that capture SUD treatment use and criminal behavior. An alternative to individual-level analysis is to estimate the aggregate effect of SUD treatment on crime:

$$\boldsymbol{Crime\ Rate}_{j,t} = f(\boldsymbol{SUD\ Treatment\ Rate}_{j,t}, Law\ Enforcement\ Level_{j,t}, Z_{j,t}) \quad (5)$$

where the local aggregated rate of crimes $Crime\ Rate_{j,t}$ is a function of the local aggregated rate of SUD treatment use $SUD\ Treatment\ Rate_{j,t}$, the local aggregated leve of law enforcement resources $Law\ Enforcement\ Level_{j,t}$, and other aggregated factors that are correlated with both the SUD treatment rate and crime rate.

Our study estimates the reduced-form effect of increasing SUD treatment use on reducing crimes. Although we cannot explicitly estimate substance use, we assume that this reduced-form effect of increasing SUD treatment use on reducing crime comes mainly from the reduction in substance use. While our approach does not provide a direct estimate of the amount of crime that arises from more substance use problems, it provides a direct answer to the policy question of how much crime would be reduced by higher level of SUD treatment use. The estimated crime reduction effect of increasing SUD treatment use can, in turn, be used in comparison to other crime-reduction policies on a cost-benefit basis.

As shown in Equations (1) to (4), both treatment and enforcement can be potential strategies to reduce substance use and crime. With respect to the crime-reduction effect of enforcement, existing evidence has suggested that enforcement may neither be an effective nor a cost-effective strategy.

First, enforcement may not effectively raise the prices of substances beyond the short term. Although some enforcement shocks may create temporary increases in the prices, their long-term equilibrium effect on price is at best modest (Caulkins Reuter 1998). Second, the effectiveness of enforcement can be further limited by the inelastic demand for substance use. A key insight from Becker and Murphy's (1988) model of rational addiction is that "adjacent complementarity" can make a rational substance user unresponsive to a temporary price increase, even a large spike (Becker and Murphy 1988, 1991)[7]. The degree of price elasticity may even be lower if time-inconsistent, present-bias preferences for substance use are taken into account (Gruber and Koszegi 2001, O'Donoghue and Rabin 1999)[8]. Third, even if we assume enforcement can increase the equilibrium price of substances and reduces substance use, at the margin enforcement may still cost more than they save. For instance, punitive approaches would impose direct costs on the criminal justice system, and a potential negative spillover into public safety costs due to an increased violence in illegal markets; the direct criminal justice costs and the spillover public safety costs are unlikely to be offset by the savings in health care costs and the costs of

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[7] According to the B-M model, "adjacent complementary" or reinforcement means that the addictive goods/bads consumed in different time periods are complements. Because of the complementarity of addictive consumption across time, an increase in the addictive stock increases the marginal utility of current addictive consumption, which in turn, increases the future utility. Therefore, as Becker and Murphy (1991) point out, "[since temporary police crackdowns on drugs] raises current but not future prices … [and it] would even lower future prices if drug inventories are built up during a crackdown period, there is no complementary fall in current use from a fall in future use. Consequently, even if drug addicts are rational, a temporary war that greatly raised street prices of drugs may well have only a small effect on drug use." (Becker and Murphy 1991, pp. 241)

[8] According to the G-K model, the self-control problem in impulsive consumption is characterized by a relatively high discounting rate over short horizons compared to the discounting rate over long horizons, which introduce a "time inconsistency" between the present and future preferences and a "present bias" to dynamic decision making. Under this time-inconsistency assumption, the demand for substance use with respect to a temporary price increase would be lower than under the B-M framework of rational, time-consistent addiction.

productivity losses related to substance use (Donohue, Ewing and Peloquin 2001; Miron 1999)[9]. Given the limited effect of enforcement on the equilibrium price of substances, the inelasitic demand for substance use in response to price increases, and the relatively high costs directly imposed on criminal justice and spilling over onto public safety, Becker, Murphy, and Grossman (2006) conclude that the current level of enforcement may far surpass the socially optimal level[10].

As an alternative to enforcement, SUD treatment is better able to reduce substance use at much lower cost, therefore more effectively and cost-effectively reducing crime. After three decades of advances in the science of the human brain (Leshner 1999, McLellan et al. 2000), contemporary neurobiology research recognizes addiction as a chronic disease of brain reward centers and ties clinical phenomena of the disease to specific neuronal mechanisms and pathological processes (Dackis and O'Brien 2005; Everitt and Robbins 2005; Kalivas and Volkow 2005). This deeper understanding of the nature of substance use and addiction has led to the development of SUD treatment services based on scientific knowledge and empirical evidence. These evidence-based services combine pharmacotherapies (e.g., medications such as naltrexone for alcohol use, methadone and buprenorphine for opioid use, etc.) with cognitive behavioral interventions, integrate medical treatment with support services (e.g., ancillary mental health services, housing

[9] In addition to the negative externalities on public safety, equity concerns have been raised, as racial profiling in arrests, prosecutions, and incarcerations may take a disproportionately heavy toll on racial minorities (Banks 2003, Bobo and Thompson 2006, Fellner 2009).

[10] As such it is difficult to justify the current drug war regime from the perspective of social welfare maximization, unless the justification is based on interest group power rather than social welfare considerations (Becker, Murphy and Grossman 2006).

assistance, social skill development, mentoring and peer support, etc.), and are tailored to individual needs (Leshner 1999). There is now clear evidence for the effectiveness of the SUD treatment: as longitudinal studies have shown, 40 to 60 percent of the clients who received recovery/rehabilitation-oriented SUD treatment are continuously abstinent from substance use, and an additional 15 to 30 percent have not resumed abuse or dependent use at follow-up one-year after treatment (McLellan et al. 2000). Furthermore, these effective services can be provided at a relatively low marginal cost and with relatively small negative externalities[11].

Another advantage of SUD treatment over enforcement is that the inelastic demand for substance use may render the marginal enforcement inefficient, but would not affect the efficiency of SUD treatment. In fact, expanded treatment may help increase the price elasticity of demand for substance use and improve the efficiency of enforcement. By alleviating the reinforcement effect of substance use, SUD treatment can reduce the degree of adjacent complementary between the marginal utility of current addictive consumption and future utility. SUD treatment can also serve as a pre-commitment device to address the self-control problem, thereby reducing the degree of time inconsistency in demand for substance use (McLellan 1996, Ainslie and Monterosso 2003). Lower degrees of adjacent complementary and time inconsistency result in a higher degree of price elasticity of

[11] There are "Not In My Back Yard" (i.e., NIMBY) concerns that the development of a SUD treatment facility in a community may reduce residential property value and bring an influx of non-locals that threaten community cohesion and place a strain on public resources. Yet, there is no empirical evidence for these claims.

demand for substance use, which in turn may improve the efficiency of the existing level of enforcement as discussed earlier (Becker, Murphy, and Grossman 2006).

3.2.2 Literature on SUD Treatment and Crime Reduction

Despite those appealing advantage of SUD treatment over enforcement in reducing substance use and crime, this area has garnered relatively little attention in the economic literature on crime reduction. Only a limited number of studies in the clinical and criminological literature have examined the crime reduction effect of SUD treatment use, and most of them have relied on individual-level self-reported crime data among substance users receiving SUD treatment. According to one of the most comprehensive meta-analyses covering empirical studies between 1965 and 1996, SUD treatment achieves, on average, a more than 50 percent reduction in the individual likelihood of committing crime (Prendergast, Podus et al. 2002).

However, concerns have been raised over both internal validity and external validity of these individual-level studies. First, selection bias may occur if those substance users who self-refer to treatment are also more self-motivated to change their behavior during and after the treatment process. Selection bias may also occur in coerced treatment regimes. Courts and other law enforcement agencies are likely to "cherry-pick" offenders with less severe addictions and less adverse life circumstances, and assign them to treatment programs in addition to or in lieu of incarceration (Chandler, Fletcher, and Volkow 2009; Taxman, Henderson, and Belenko 2009). The incentive for "cherry-picking" results from the linkage of funding for drug courts and diversion programs to their success rates. Second, “regression-to-the-mean” may further bias the positive findings if substance users tend to seek treatment when their substance use and related consequences have reached an uncomfortable intensity. In this scenario, similar behavioral changes may still be observed even in absence of treatment. Third, the reliability of self-reported crime has been called into question. This is particularly true in the tails of the distribution of criminal activity frequency: infrequent offenders tend to underreport criminal behavior and frequent offenders tend to overstate their criminal involvement (Levitt 1996). Finally, the generalizability of most individual-level studies is limited to a specific type of treatment received by a specific group of substance users in a specific geographic area.

Our study provides the first county-level and Core-Based Statistical Area (CBSA)-level estimates for the effect of increasing the SUD treatment rate on reducing violent and property crime rates. An aggregate-level analysis can alleviate the selection and self-reporting issues inherent in most individual-level studies. Moreover, an aggregate-level analysis is more generalizable and salient to policy, as it captures the population-level effect of SUD treatment use on crime reduction.

3.3 Data

Our data is a panel of annual, county-level observations between 2001 and 2008. Data sources include the Uniform Crime Reports (UCR), the National Survey of Substance Abuse Treatment Services (N-SSATS), and other nationally representative datasets that provide supplementary information on important local-level socioeconomic and policy context.

3.3.1 Dependent Variable: Crime Rates

County-level crime rates (*Crime Rate*$_{c,s,t}$) were collected annually by the Federal Bureau of Investigation (FBI) in the UCR 2001-2008, and were calculated based on the number of crimes reported to the police of all law enforcement agencies within each given county c over an entire calendar year t[12] (*Crime Rate*$_{c,s,t}$: number of crimes reported to all police agencies per 1,000 residents).

UCR county-aggregate crime data are available for the eight Part I crime categories, namely criminal homicide, forcible rape, aggravated assault, robbery, burglary, larceny theft, motor vehicle theft, and arson. The first four crime categories are collectively referred to as violent crime, while the latter four as property crime[13].

3.3.2 Primary Independent Variable: SUD treatment rate

[12] The UCR 2001-2008 uses the following imputation procedures to deal with the missing data: the crime data for an agency reporting 12 months were used as submitted. Data for an agency reporting 3 to 11 months were augmented by a weight of 12 divided by the number of months reported; data for an agency reporting 1 to 2 months were imputed based on the other agencies located in the same geographic stratum within a state and reporting 12 months of complete data. No imputation was conducted for any agency missing data for all 12 months (Lynch and Jarvis 2008)

[13] It has been well-recognized that the UCR data are the product of a set of social processes such that some crimes become “official” and “public facts” while others do not. Legal severity, victim-offender relationships, desires of the complainant, and the extent to which citizens and police see an incident as a public or private matter are all criteria related to reporting (Gove, Hughes, and Greerken 1985). Nonetheless, Gove, Hughes, and Greerken (1985) provide a strong argument that the UCR provides valid and reliable indicators of the Part I (index) crimes, which consist of relatively severe crimes likely to pass through the citizen and police filters and officially reported. Furthermore, if the measurement error in UCR data is simply random noise, our estimates would still be consistent (albeit with less precision), since crime rates are the dependent variables. To the extent that we obtain similar estimates from different sources of variation in the data (e.g., county- or CBSA-level analysis, instrumenting with one or both policy instruments, with or without state-specific linear trends), the measurement error is unlikely to seriously bias our estimates (Katz, Levitt, and Shustorovich 2003).

The county-level SUD treatment rate was derived from facility-level information on annual SUD treatment counts in the N-SSATS 2000, 2002-2008[14]. N-SSATS covers all known specialty SUD treatment facilities[15] across the United States and achieved 92-95 percent response rates during the study period, allowing for a nearly complete enumeration of specialty SUD treatment services in the United States.

All surveyed facilities were requested to report the total SUD treatment counts in the most recent 12 months prior to the survey. N-SSATS specified that the treatment count should only include the initial entry of a client into treatment; subsequent visits to the same service or transfer to a different service within a single continuous course of treatment were excluded. The facility-level treatment counts were then aggregated to each county c in each year t to determine the county-level annual SUD treatment rate ($SUD\ Treatment\ Rate_{c,s,t}$: number of SUD treatment entries into all specialty SUD treatment facilities per 1,000 residents).

3.3.3 Other Controls

County-level covariates include demographic characteristics, economic conditions, and law enforcement resources. Demographic characteristics including age distribution and

[14] Note that in 2002, the N-SSATS survey date was changed from September to March to enhance the response rate, leaving a gap period from September 2000 to March 2001 with no data collected. Accordingly, the annual treatment data (representing SUD treatment from April 2001 to March 2002) was matched with the same-year annual crime data (representing reported crimes from January 2002 to December 2002) for the year of 2002 and for each year afterward; while the 2000 treatment data (representing SUD treatment from October 1999 to September 2000) was paired with the 2001 crime data (representing crimes from January 2001 to December 2001).

[15] Specialty SUD treatment facility, according to N-SSATS, is defined as a hospital, a residential SUD facility, an outpatient SUD treatment facility, a mental health facility with an SUD treatment program, or other facility with an SUD treatment program providing the following treatment services: (a) Outpatient, inpatient, or residential/rehabilitation SUD treatment; (b) Detoxification treatment; (c) Opioid treatment programs (OPT) such as methadone and L-α-acetyl-methadol (LAAM) maintenance; or (d) Halfway house services that include SUD treatment.

racial/ethnic composition of the population were measured as the percentage of county residents who were (1) between the ages of 15 and 34[16], (2) Black, (3) Hispanic/Latino, (4) Asian, and (5) members of other racial/ethnic groups. Economic conditions were measured as the county's (6) median household income, (7) poverty rate[17], and (8) unemployment rate[18]. Law enforcement resources, another mechanism by which crime could potentially be deterred, were measured as (9) the number of sworn officers per 1,000 residents[19]. We used both contemporaneous and one-year lagged values of law enforcement resources to account for the immediate and delayed effect of their deterrence on crime (Levitt 1997). The demographic and economic measures were drawn from the Area Health Resource File; the law enforcement measure was taken from the UCR.

Furthermore, we included contemporaneous and one-year lagged values[20] of state government expenditures in several key domains to account for the public investment that may help reduce crime. Measures of state government expenditures include the dollar per capita spending on: (i) education, (ii) police protection and correction, (iii) hospital and

[16] Adolescents and young adults aged 15-34 are at high risk of participating in substance use (SAMHSA 2011) and in substance-related crimes (Brame and Piquero 2003).

[17] Poverty rate is calculated for the civilian noninstitutionalized population based on household income, household size, and household composition, relative to a set of dollar value thresholds called the "federal poverty level (FPL)". Institutionalized persons, those in military group quarters, and those living in college dormitories, and unrelated children under the age of 15 are excluded from the numerator and denominator when calculating the poverty rate.

[18] Unemployment rate is calculated as the number of unemployed persons (aged 16 and above) divided by the number of persons in the labor force (aged 16 and above). The numerator and denominator do not include institutionalized persons or those without employment who are not seeking employment.

[19] Sworn officers, according to UCR, are defined as full-time, sworn personnel with full arrest powers including the chief, sheriff or other head of the agency as of October 31.

[20] We conducted extensive checks for the lag structure of state government expenditures. One might expect, for instance, that the expenditure on education or other prevention pathways may have a delayed effect on crime rates, so we assessed whether spending levels two and three years prior affected crime rates. Two- and three-year lagged values of state government expenditures were neither individually nor jointly significant in predicting crime rates, and thus excluded from our model specifications.

health, and (iv) welfare and other domains (e.g., government administration, highways, natural resources, etc.). The information on state government expenditures was compiled by the Census Bureau from the Annual Survey of State Government Finances. Two additional state-level measures were included to capture other relevant changes in the state policy environment during the study period: (v) state excise tax rates on beer[21], and (vi) amount of the Substance Abuse Prevention and Treatment Block Grant (SAPTBG) allocated to states that may affect their SUD treatment system capacity. The information on state beer tax and SAPTBG funding was compiled by the Alcohol Policy Information System (APIS) and the Treatment Improvement Exchange (TIE) database, respectively.

3.4 Estimating the Effect of the SUD treatment rate on Crime Rate Using OLS

To estimate the effect of the SUD treatment rate on crime rates, we begin with a simple ordinary least squares (OLS) regression based on the following specification:

$$\textbf{\textit{Crime Rate}}_{c,s,t} = \beta_1 + \beta_2\ \textbf{\textit{SUD Treatment Rate}}_{c,s,t} + \beta_3 X_{1\ c,s,t} + \beta_4 X_{2\ s,t} + \rho_c + \tau_t + \varepsilon_{c,s,t} \quad (6)$$

where c denotes county, s denotes state, t denotes year. ρ_c represents county fixed effects and τ_t represents year fixed effects. The two-way (i.e., county and year) fixed effects account for the time-invariant county heterogeneity and the national secular trend in crime rates. $X_{1\ c,s,t}$ is a time-varying, county-level vector of demographic, economic and law enforcement factors that may be correlated with both the local crime rates and the local

[21] State beer tax is defined as specific excise taxes levied per gallon at the wholesale or retail level.

SUD treatment rate. $X_{2\ c,s,t}$ is a time-varying state-level vector of government expenditures on crime-related functions, beer tax rates, and the SAPTBG funding amount. Standard errors were clustered at the state level to correct for serial correlation. The clustered standard errors allow for arbitrary within-state correlation in the error terms but assume independence across the states (Bertrand, Duflo et al. 2004).

Equation 5 was estimated using each Part I crime category as the dependent variable in eight separate models. Equation 5 was also estimated for two additional models in which the dependent variable was the sum total of the four violent crimes or four property crimes, respectively. In theory, the crime-reduction effects of SUD treatment should be concentrated among crimes related to substance use, and in which the substance users involved would be likely to seek SUD treatment if available and within their budget constraint. We would therefore expect the effect of an increased the SUD treatment rate to be concentrated in lower-level property and violent crimes such as theft, robbery and assault, but not in crimes typically committed by more ‘hardcore’ criminals such as homicide and rape.

The first two columns of Table 3.2 presents the OLS estimates for two analytic samples: (1) an unbalanced panel consisting of all 23,537 non-missing observations (i.e., 3,016 counties[22] over an average of 7.8 years); and (2) a balanced panel limited to 22,328 observations (i.e., 2,791 counties that had all data available over the 8-year period).

[22] The original sample includes all 3,143 counties across the U.S. 127 counties with missing data on any study variable for at least 7 years were excluded from the analysis, resulting in the inclusion of 3,016 counties in the unbalanced panel.

Note that the primary unit of analysis in our study is county-year. Although county is the smallest geographic area identified in the UCR and the N-SSATS data, it may be too small to capture the potential area where people engage in SUD treatment and crime. In this sense, the crime-reduction effect of the increased SUD treatment rate in one county may spill over into the neighboring counties. To check the robustness of the county-level analysis, we aggregated the data to a higher level, the Core-Based Statistical Area (CBSA) level. A CBSA is a geographic area defined by the Office of Management and Budget (OMB) based around an urban center of at least 10,000 residents and adjacent areas that are socioeconomically tied to the urban center as determined by commuting patterns. The term "CBSA" refers collectively to both metropolitan statistical areas (MSAs) and micropolitan statistical areas (µSAs). We excluded the 1354 non-CBSA rural counties, which only account for 4 percent of the overall SUD treatment rate and 6 percent of the overall crime rate. We converted the remaining 1788 counties to 941 CBSAs (i.e., 335 MSAs and 526 µSAs), and subsequently separated those CBSAs across multiple states[23] to accommodate the state-level instrumental variables we would introduce later to our analysis (see Sections 3.5 and 3.6). The final CBSA-level samples thus include an unbalanced panel of 981 CBSA-like units over 7.9 years and a balanced panel of 928 CBSA-like units over 8 years.

[23] For instance, Boston-Cambridge-Quincy is a CBSA that consists of 5 Massachusetts counties and 2 New Hampshire counties. Given that Massachusetts implemented an HIFA-waiver expansion between 2007 and 2008, while New Hampshire implemented an SUD parity mandate between 2004 and 2008, we aggregated the 5 Massachusetts counties to a CBSA-like group, and aggregated the 2 New Hampshire counties to another CBSA-like group.

According to the OLS estimates, the local SUD treatment rate is unrelated to most of the local crime rates. At the county level, a statistically significant crime-reduction effect of the SUD treatment rate was only found in the case of aggravated assault. The estimated effect size, however, is very small: an increase in the SUD treatment rate by one per 1,000 residents only reduced the aggravated assault rate by about 0.002 per 1,000 residents. Translating the estimated marginal effect into percentage change and elasticity, we found that a 10 percent relative increase in the SUD treatment rate reduced the aggravated assault rate by a relative 0.1 percent at the county level, equivalent to a treatment-crime elasticity of -0.01. The CBSA-level estimates are similar to the county-level estimates, except for a statistically significant reduction in the robbery rate shown in some of the specifications. However, the effect size is even smaller for robbery than for aggravated assault: a 10 percent relative increase in the SUD treatment rate reduced the robbery rate by a relative 0.06 percent at the CBSA level, or a treatment-crime elasticity of -0.006. Neither of the naïve estimates indicates any economically meaningful relationship between the local SUD treatment rate and crime rates.

3.5 HIFA-Waiver Expansions and SUD Parity Mandates: Instrumental Variables

3.5.1 Endogeneity of the SUD treatment rate with Respect to Crime Rates

In our OLS estimation, the effect of the local SUD treatment rate on crime rates is identified using county and year fixed effects to isolate the within-county variations in crime rates over time. Nonetheless, we suspect that the OLS estimates may underestimate the crime-reduction effect of the SUD treatment rate for multiple reasons. First, reverse causality may exist as higher crime rates translate back to a higher SUD treatment rate through drug courts or diversion programs offered to a select group of non-violent offenders in need of treatment. Failing to address this "structural endogeneity" may result in a downward-biased OLS estimate[24]. Second, we cannot measure important variables that may be correlated both with the SUD treatment rate and with crime rates. Some of these omitted variables, such as underlying changes in the county-level prevalence of substance use and the fluctuations in market factors[25]may affect the SUD treatment rate and crime rates in the same direction[26]. This unobserved heterogeneity may also bias the OLS estimates towards the null hypothesis.

To address these modelling concerns we employ a set of instrumental variables that are strongly related to SUD treatment, but are otherwise unrelated to crime. The instruments are two state-level policy shocks that occurred during the 2000s, namely the Health Insurance Flexibility and Accountability (HIFA)-waiver expansions and SUD health insurance parity mandates. Below we provide the institutional/intuitive support for the credibility of our policy instruments. Sections 3.6.1 and 3.6.3 proceed with the statistical evidence on the strength and validity of the instruments.

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[24] The naïve solution of replacing or instrumenting the endogenous variable with its lagged form is problematic if the error terms are in effect serial-correlated.

[25] Reliable data on the market price of substances are difficult to obtain especially for illicit drugs. The most commonly used source is the U.S. Drug Enforcement Administration's System to Retrieve Information from Drug Evidence (STRIDE) dataset. However, STRIDE prices may not represent market prices, and are consequently not reliable for the purpose of economic and policy analysis (Horowitz 2001). As French and Popovici (2011) pointed out, "part of the difficulty here is that conventional prices for illicit drugs are not readily available and alternative measures are not yet found."

[26] For instance, a surge in methamphetamine price as a result of a crackdown on local labs may be correlated with an increase in the SUD treatment rate, and also correlated with an increase in crime rates: some methamphetamine users would respond to the higher price by seeking treatment to help quit drug use, whereas others may resort to crime to help fund their addiction.

3.5.2 Treatment Gap & Limited Insurance Coverage for SUD Treatment

An estimated 23 million Americans suffered from SUDs in 2010, of which only 11 percent received specialty SUD treatment for their condition (SAMHSA 2011). The lack of health insurance coverage and the lack of adequate insurance benefits for SUD treatment were cited as major financial barriers to SUD treatment among those who perceived a need for treatment (SAMHSA 2011).

People with SUDs are overrepresented among the uninsured, largely because they are more likely to be out of the workforce, unemployed or part-time working poor who can neither obtain insurance through an employer-sponsored plan nor afford insurance in the individual market (Wu, Kouzis, and Schlenger 2003). And among them, only a small proportion who meet the "categorical eligibility" criteria[27] are qualified for Medicaid coverage. Left uninsured, those with SUDs are unable to get access to the treatment they need.

While the lack of health insurance coverage may pose financial barriers to SUD treatment for the uninsured, those covered by private health insurance can also face financial barriers due to the inadequate insurance benefits for SUD treatment. Although benefits for SUD treatment are typically covered by private health insurance,

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[27] As a means-tested health insurance program for the most vulnerable populations in society, Medicaid traditionally covered only certain categories of families and individuals. Childless adults without disabilities were not eligible for Medicaid in most states regardless of their income level. The income eligibility threshold for adult members of poor families was much higher than the threshold for their dependent children. During the early 2000s, the national median income threshold for an adult from a low-income family was 60% of the FPL; in over 20 states the threshold was lower than 50% of the FPL (KFF 2013). Furthermore, a substance user who is disabled may still be deemed ineligible for Medicaid if his/her disability was solely caused by substance use (KFF 2013). The expansions of Medicaid eligibility during the late 1980s and the 1990s were largely targeted at children from low-income families and pregnant women, thus having little impact on SUD treatment use among the adult population.

discriminatory restrictions are often imposed on these SUD benefits. In 2008, SUD benefits in more than 80 percent of private health plans were subject to higher cost sharing or more treatment limitations than benefits for comparable medical/surgical treatment (BLS 2009).

During the past decade, two sets of state-level policies have significantly reduced the financial barriers to SUD treatment and consequently increased the SUD treatment rate. These are the Health Insurance Flexibility and Accountability (HIFA)-waiver expansions and SUD parity mandates.

3.5.3 Insurance Expansions under HIFA Waivers

The Health Insurance Flexibility and Accountability (HIFA) initiative was introduced by the Bush administration in August 2001 to encourage innovative approaches by states to reducing the number of uninsured Americans. The HIFA initiative enables states to apply for waivers that provide a high level of policy flexibility and federal matching funds to reshape state Medicaid programs and State Children's Health Insurance Programs (SCHIPs) (CMS 2001). Several states took advantage of the HIFA waivers to expand insurance coverage to people who did not fall into the traditional welfare-based categories: low-income adults who were nondisabled, childless, or from qualified poor families (Coughlin, et al. 2006). The expanded income eligibility threshold varied from state to state, up to a maximum of 200% of the FPL[28](Atherly, Coulam et al. 2012).

[28] Federal matching funds were provided for all low-income adults with family incomes below up to 200% FPL if states included them in the expansion. The actual income threshold of the expanded Medicaid eligibility is left to the state discretion.

As noted by Atherly and colleagues (2012), fifteen states received approval for HIFA waivers between 2001 and 2008, and seven of the fifteen waiver states implemented actual and comprehensive insurance expansions to low-income adults. Across these seven states, the authors found that the HIFA-waiver expansions increased the probability of being insured by 6 percentage points, or a relative 13 percent among the targeted low-income adult populations (Atherly, Coulam et al. 2012). Sommers and colleagues (2012) focused on the three “early HIFA states” that adopted expansions between 2001 and 2002, and found a 14 percent decrease in the rate of financial-related delays in care attributable to the HIFA-waiver expansions (Sommers, Baicker et al. 2012). If the HIFA-waiver expansions improved insurance coverage among low-income adults and improved their health care use in general, they should also have the potential for improving their use of SUD treatment.

3.5.4 Parity Mandates for SUD treatment

To address the discriminatory restrictions in SUD benefits in private health insurance market, SUD parity was first introduced during the early 1980s in several states, primarily in the South. The SUD parity mandates have since been enacted by more than half of the states. These mandates require private group health plans[29] to provide benefits

[29] Most state-level parity laws apply only to employment-based group health plans, leaving the individual (non-employment based) health insurance market unregulated. Some parity laws also exempt small employers with fewer than 50 or 20 employees. Moreover, the federal pre-emption by the Employee Retirement Income Security Act (ERISA) of 1974 does not allow state legislatures to impose health insurance regulations on self-insured business.

for SUD treatment that are no more restrictive than for medical/surgical treatment (SAMHSA 2006).

Between 2000 and 2008, ten states implemented SUD parity laws mandating insurance benefits for SUD treatment to be offered on par with those for comparable medical/surgical treatment, with respect to cost sharing (e.g., deductibles, copayments, coinsurance, and out-of-pocket expenses), treatment limitations (e.g., annual or lifetime limits on number of visits or hospital days), or both (SAMHSA 2006). Wen and colleagues (2013) found that the implementation of state parity mandates increased state-aggregate SUD treatment rate by a relative 9 percent in specialty SUD treatment facilities. Dave and Mukerjee (2011) assessed a set of broadly defined behavioral health parity laws, and they found that state implementation of a parity mandate was associated with a reduction in uninsured admissions and out-of-pocket costs for people treated in specialty SUD treatment facilities that received public funding. Taken together, existing evidence on parity mandates suggests that, by requiring SUD benefits to be offered on par with comparable medical/surgical benefits, SUD parity mandates may improve SUD treatment use.

3.6 Re-estimating the Effect of the SUD treatment rate on Crime Rates Using TSLS

3.6.1 Estimating the Effect of Instrumental Variables on Endogenous SUD treatment rate

We created two state-level dichotomous indicators ($HIFA_{s,t}$ and $Parity_{s,t}$) to capture the implementation of HIFA-waiver expansions in four states[30] (i.e., Illinois, 2003-2008; Maine, 2003-2008; New Mexico, 2006-2008; and Massachusetts 2007-2008) and the implementation of SUD parity mandates in seven states[31] (i.e., Montana 2003-2008, Rhode Island 2003-2008, Maine 2004-2008, New Hampshire 2004-2008, Oregon 2007-2008, Wisconsin 2005-2008, and West Virginia 2005-2008). $HIFA_{s,t}$ and $Parity_{s,t}$ were assigned a value of 1 for each full year subsequent to the year in which the legislation was first implemented or improved[32].

The effect of HIFA-waiver expansions and parity mandates on the endogenous SUD treatment rate were estimated using a two-stage least squares (TSLS) regression, based on the following specifications of the first stage:

$$\boldsymbol{SUD\ Treatment\ Rate_{c,s,t}} = \alpha_1 + \alpha_2\,\boldsymbol{HIFA_{s,t}} + \alpha_3\,X_{c,s,t} + \alpha_4\,X_{s,t} + \rho_c + \tau_t + \varepsilon_{c,s,t} \quad (7)$$

[30] Oregon in 2002 and Michigan in 2004 also expanded Medicaid programs under HIFA waivers. However, the expansion program in Michigan, the Adult Benefits Waiver (ABW), does not cover specialty SUD treatment. It only covers medically necessary mental health services provided through Community Mental Health Centers. Oregon's expansion program, the Oregon Health Plan Standard (OHP-S) initially covered specialty SUD treatment. In response to a growing fiscal crisis and special interest power, Oregon closed new enrollment to the OHP-S during the subsequent year and eliminated SUD benefits for the enrollees remaining in the program. (Coughlin et al. 2006; Oberlander 2007) Therefore Oregon and Michigan were not considered as "HIFA states" in the study.

[31] "Parity states" included the states that first implemented SUD parity mandates during the study period and those that improved the comprehensiveness of their laws during the study period. Although the parity mandates differ in their comprehensiveness (i.e., full parity, partial parity, and parity-if-offered), we created a single generic indicator to capture the implementation of any SUD parity mandate during the study period regardless of its comprehensiveness and relative improvement in its comprehensiveness. Note that among the 7 "parity states", Wisconsin implemented parity-if-offered in 2005; Montana and New Hampshire implemented partial parity in 2003 and 2004, respectively; West Virginia implemented full parity in 2005; Rhode Island (2002), Maine (2003), and Oregon (2007) improved their parity mandates from partial parity to full parity (Wen 2013). In an alternative specification, we also created three indicators for each level of comprehensiveness of the laws, which did not significantly change the F-statistics in the first-stage TSLS (not shown).

[32] Note that HIFA-waiver expansions in Arizona and New York and SUD parity mandates in Kentucky, Michigan and Delaware were implemented since 2001, which leaves almost no pre-implementation period for these states. Thus we did not classify them as "HIFA states" or "parity states".

$$\boldsymbol{SUD\ Treatment\ Rate}_{c,s,t} = \alpha_1 + \alpha_2\ \boldsymbol{HIFA}_{s,t} + \alpha_3\ \boldsymbol{Parity}_{s,t} + \alpha_4\ X_{c,s,t} + \alpha_5\ X_{s,t} + \rho_c + \tau_t + \varepsilon_{c,s,t} \quad (8)$$

Equation 6 estimates the effect of HIFA-waiver expansions alone on the SUD treatment rate, while Equation 7 estimates the effect of both instruments.[33] In both models, we included ρ_c and τ_t to adjust for the time-invariant county heterogeneity and the national secular trend. We also included the full set of covariate vectors $X_{c,s,t}$ and $X_{s,t}$ to account for the time-varying county-level and state-level confounders. Standard errors in the first stage were clustered at the state level to correct for the serial correlation.

The bottom panel of Table 3.3 presents the first-stage TSLS regression estimates at the county level for the unbalance panel (Column 1 and 2) and the balanced panel (Column 3 and 4). The implementation of HIFA-waiver expansions alone increased the county-level SUD treatment rate by 2.4 to 2.5 per 1,000 residents, equivalent to a relative 19 to 20 percent increase in treatment rate. The implementation of an SUD parity mandate (when the HIFA indicator was also included) increased the SUD treatment rate by 0.9 to 1.0 per 1,000 residents, or a relative 7 to 8 percent increase. The F-statistics across all models exceed the critical values for Stock and Yogo (2002) weak instrument test[34].

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[33] The implementation of SUD parity mandates alone also significantly increased the SUD treatment rate. Although individually significant at the 0.05 level, the F-statistics were only 3.7 and 5.4 for this specification, indicating that it was a potentially weak instrument. Therefore, we did not use $Parity_{s,t}$ as an instrument on its own in our main results.

[34] We also aggregated the data to the state level and the pre/post two-time period and re-estimated the effect of policy instruments on the SUD treatment rate. We used Donald and Lang (2007) method coupled with the two-step procedure described in Bertrand, Duflo and Mullainathan (2001, pp. 267) to accommodate the different effective times of the policies. Despite such an approach being quite restrictive, we found that the implementation of HIFA-waiver expansions alone increased the state-level SUD treatment rate by 2.47 per 1,000 residents (S.E.=0.89, t=2.80), with an F-statistic of 7.8. When including both policies simultaneously, the implementation of HIFA-waiver expansions increased the treatment rate by 2.33 per 1,000 residents (S.E.=1.02, t=2.28); the implementation of SUD parity mandates increased the SUD treatment rate by 1.73 per 1,000 residents (S.E.=0.58, t=3.01), with an F-statistic of 6.6.

3.6.2 Estimating the Effect of the SUD treatment rate on Crime Rates: Main Results

We re-estimated the effect of the SUD treatment rate on crime rates using the TSLS, treating the SUD treatment rate as endogenous and instrumenting it with the policy indicators of HIFA-waiver expansions and SUD parity mandates. In the second stage we replaced the observed values of *SUD Treatment Rate*$_{c,s,t}$ in Equation 8 with its predicted values derived from the respective first stage. The predicted values of *SUD Treatment Rate*$_{c,s,t}$ capture the exogenous variation in the county-level treatment rate induced by the two state-level policies:

$$\textbf{Crime Rate}_{c,s,t} = \beta_1 + \beta_2\, \textbf{SUD Treatment Rate}_{c,s,t}\, \textbf{(Predicted)} + \beta_3 X_{c,s,t} + \beta_4 X_{c,s,t} + \rho_c + \tau_t + \varepsilon_{c,s,t} \quad (9)$$

The top panel of Table 3.3 presents the second-stage TSLS estimates for the county-level crime rates when instrumenting with HIFA-waiver expansions alone (Column 1 and 3), and when instrumenting with both policies (Column 2 and 4). The TSLS estimates suggest that a statistically significant crime-reduction effect is present in three subcategories, namely robbery, aggravated assault, and larceny theft. An increase in the SUD treatment rate of 1 per 1,000 residents reduced the robbery rate by 0.03 per 1,000 residents. The estimated effect is consistent across all specifications. Moreover, an increase in the SUD treatment rate also reduced the aggravated assault rate, with the effect size ranging from -0.1 to -0.2 per 1,000 residents. We also found a significant reduction in property crimes, which was largely driven by a -0.4 to -0.5 per 1,000 residents estimated effect of increased SUD treatment on larceny theft.

Translating the estimated marginal effects into percentage changes, a 10 percent relative increase in the SUD treatment rate led to a relative 3 percent reduction in the robbery rate, a relative 4 to 9 percent reduction in the aggravated assault rate, and a relative 2 to 3 percent reduction in the larceny theft rate. Stated another way, the treatment-crime elasticity is -0.3 for robbery, -0.4 to -0.9 for aggravated assault, and -0.2 to -0.3 for larceny theft. The sizeable crime-reduction effect of SUD treatment on robbery and aggravated assault suggests that, through reduced substance use, SUD treatment may reduce the risk of personal violence that is likely to occur as a result of intoxication, which corresponds to Goldstein (2003)'s pharmacological hypothesis. The sizeable effect on robbery and larceny theft suggests that SUD treatment may also reduce the motivation for financing substance use habits through illegal activities, which corresponds to Goldstein (2003)'s economic motivation hypothesis.

Table 3.3 also contains the TSLS estimates at the CBSA level. The first stage indicates that the policy instruments remain strong, and the crime-reduction effect of the increased SUD treatment rate remains significant for the rate of robbery, aggravated assault, and larceny theft. However, the effect sizes in these specifications are smaller, especially for aggravated assault rate.

Generally the TSLS estimates are robust to the balancing of panels and the re-aggregation of data from the county level to the CBSA level. Note, however, that the simple OLS estimates are substantially different in magnitude from the TSLS estimates across all crime subcategories, an indication of omitted variable bias in the OLS estimates. Moreover, the differences between the OLS estimates and the TSLS estimates are larger for the subcategories of property crimes than for those of violent crimes, which further suggests that the reverse causality from non-violent offense to court-coerced SUD treatment may also bias the OLS estimates.

3.6.3 Checking for the Validity of the Instrumental Variables

Given the novelty of our instrumental variables and the dramatic changes from the OLS estimates to the TSLS estimates, the validity of the instruments warrants closer scrutiny. The number of instruments we identified allows for an overidentification test of the exclusion restrictions. The results from these tests (not shown) lend support to the exogeneity of both instruments with respect to crime rates of all subcategories. In addition to the overidentification test, specifications with a series of lagged and leading policy indicators were estimated (Table 3.4) to check for the policy endogeneity of our two instruments. Only the contemporaneous and lagged policy indicators have a significant effect on the SUD treatment rate and crime rates[35], while all the leads have insignificant effects with effect sizes close to zero[36]. This indicates that it is the policy shocks of HIFA-waiver expansions and SUD parity mandates that drive the changes in the SUD treatment rate and subsequent reduction in crime rates, rather than some past shock to the SUD treatment rate and/or crime rates leading to the adoption of the policies that expanded health insurance coverage for those with SUD. As such, the policy instruments we use appear to be exogenous.

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[35] Table 3.4 only presents the estimated effects on total crime rate. We also replaced the total crime rate with the rates of eight crime subcategories and found similar results.

[36] In addition to the one- and two-year leads, we also included three-year leads and more. The effects of these leads on the SUD treatment rate and crime rates were virtually zero.

To further test the validity and strength of our instruments, we added state-specific linear time trends $\rho_s t$ in both stages of the TSLS regressions to account for the unobserved state-level factors that evolve over time at a constant rate (e.g., public sentiment towards crime and addiction). We found that in the first stage, the effect of the implementation of HIFA-waiver expansions on the SUD treatment rate was robust to the inclusion of state-specific linear trends (Table 3.5 bottom panel). With regard to the second stage, the point estimates of the effect of the SUD treatment rate on crime rates are similar to the main results, but these effects are not precisely estimated (Table 3.5 top panel).

3.7 Discussion

SUD treatment holds the potential not only to reduce individual substance use, but also to promote public safety by reducing crime. One contribution of our study is that we uncovered a heretofore unrecognized relationship between the implementation of HIFA-waiver expansions and the increase in the SUD treatment rate. While this finding is interesting in and of itself, it also provides a potential avenue for solving the issue of joint determination of SUD treatment and crime that may seriously bias the simple OLS estimates towards zero. By instrumenting with the HIFA-waiver insurance expansion policy and the SUD parity mandate, we were able to address the endogeneity of the SUD treatment rate with respect to crime rates. We find a sizable effect of the increased SUD treatment rate on crime reduction.

The study findings highlight that a relative 10 percent increase in the SUD treatment rate can reduce the robbery rate by 3 percent, reduce the aggravated assault rate by 4 to 9 percent, and reduce the larceny theft rate by 2 to 3 percent. To better understand the public policy implications of these estimates, we further provide a speculative cost-benefit calculation.

The best available estimates of the costs of crime come from Rajkumar and French (1997) and McCollister et al. (2010), which estimate the per-offense cost of crime across all major crime categories. These estimated costs of crime attempt to capture the direct tangible losses to crime victims and to the criminal justice system, the opportunity costs associated with the criminal's choice to engage in illegal rather than legal activities, as well as indirect and intangible losses suffered by crime victims, including pain and suffering, decreased quality of life, and psychological distress. Based on Rajkumar and French (1997) and McCollister et al. (2010), the annual costs are roughly $15 billion to $19 billion for robbery, $8 billion to $25 billion for aggravated assault, and $65 billion to $92 billion for larceny theft (2008 dollars). Given that the national expenditures for SUD treatment is approximately $16 billion annually (Mark, Levit et al. 2007), a 10 percent increase in treatment rate at an average cost of $1.6 billion can yield an average benefit of $2.5 billion to $4.8 billion from reducing crime rates. The benefit-cost ratio of SUD treatment with respect to crime reduction ranges from 1.6 to 3.0. To put these numbers into context, incarceration, which has been attributed to one third of the crime decline during the 1990s, has a benefit-cost ratio centered around 1.5 (Levitt 1996; Levitt 2004). Therefore, SUD treatment not only appears to be a more effective but also a more cost-effective alternative to incarceration at reducing crime.[37]

[37] A further consideration is that the preliminary cost-benefit calculation reflects the national average cost of providing SUD treatment, rather than the marginal costs of an additional substance user entering treatment in response to the policies aimed to improve access to care. We expect the latter to be even lower, and we plan to conduct a more accurate cost-benefit analysis based on additional sources such as Medicaid claim data.

On August 12, 2013, during a speech to the American Bar Association's House of Delegates, Attorney General Eric Holder called for a "sweeping, systemic change" to the "ineffective and unsustainable" drug war regime. The centerpiece of Holder's new agenda is to scale back mandatory minimum sentences for low-level drug offenders, and to replace incarceration with SUD prevention and treatment. Among the 700,000 inmates released annually from federal and state jails/prisons, an estimated two thirds have behavioral health problems including SUDs, and under the ACA more than half of those former inmates are expected to gain health insurance coverage and access to care (Cuellar and Cheema 2012)[38]. Our study findings suggest that expanding insurance coverage and benefits for SUD treatment is an effective policy lever to encourage treatment use, and a higher level of SUD treatment use can cost-effectively reduce crime.

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[38] Cuellar and Cheema (2012) estimated that 730,000 inmates were released from federal and state prisons during 2009; among them 245,000 could enroll in Medicaid under the ACA expansion, and 172,000 could be eligible for federal tax credits to defray the cost of purchasing insurance from the exchanges. Furthermore, the combination of Medicaid coverage and the receipt of behavioral health services including SUD treatment is shown to be associated with a 16 percent reduction in recidivism rate and fewer jail days in the one-year follow-up period, according to a study on inmates with serious mental illness released from jails in King County, Washington and Pinellas County, Florida (Morrissey et al. 2007). The positive findings, however, may be upward biased by the selection issue we mentioned in Section 3.2.2.

TABLE 3.1 DESCRIPTIVE SUMMARY OF THE STUDY VARIABLES

Summary Statistics	**County-Level**	**CBSA-Level**
	Mean (S.D.)	*Mean (S.D.)*
DEPENDENT VARIABLES:		
Total Crime Rate (per 1,000 residents)	40.11 (17.80)	41.42 (13.80)
Violent Crime	4.93 (3.36)	4.85 (2.49)
Criminal Homicide	0.06 (0.06)	0.05 (0.04)
Forcible Rape	0.36 (0.37)	0.38 (0.29)
Robbery	1.51 (1.41)	1.37 (1.00)
Aggravated Assault	3.01 (2.06)	3.05 (1.69)
Property Crime	35.18 (15.45)	36.56 (12.35)
Burglary	7.44 (3.83)	7.82 (3.33)
Larceny Theft	23.40 (10.19)	24.40 (8.55)
Motor Vehicle Theft	4.08 (3.29)	4.08 (2.65)
Arson	0.25 (0.21)	0.27 (0.19)
PRIMARY INDEPENDENT VARIABLE:		
SUD Treatment Rate (per 1,000 residents)	12.81 (10.24)	13.15 (8.49)
COVARIATES:		
County Demographics, Economics, & Enforcement:		
% Age 15-34	27.71 (3.99)	27.96 (3.61)
% African/Black	12.78 (13.26)	10.72 (10.27)
% Hispanic/Latino	13.91 (15.76)	15.15 (16.86)
% Asian	4.32 (5.62)	4.14 (5.75)
% Other Racial/Ethnic Origins	2.74 (4.01)	2.97 (4.09)
$ Median Family Income ($1,000)	47.94 (12.88)	46.73 (10.08)
% Poverty	12.56 (5.05)	12.76 (4.30)
% Unemployment	5.14 (1.95)	5.23 (2.00)
% Sworn Officers	2.33 (2.54)	2.61 (2.02)
State Government Expenditures ($1,000 per capita):		
$ Education	15.43 (3.20)	15.52 (3.28)
$ Police Protection & Correction	1.83 (0.44)	1.83 (0.45)
$ Health & Hospital	3.24 (1.22)	3.26 (1.24)
$ Welfare & Other Domains	22.62 (6.44)	22.44 (6.23)
$ State Beer Excise Tax Rates ($ per gallon)	0.23 (0.16)	0.24 (0.17)
$ State SAPTBG Funding ($ per capita)	5.52 (0.78)	5.57 (0.84)

TABLE 3.2 ESTIMATED EFFECT OF THE SUBSTANCE USE DISORDER (SUD) TREATMENT RATE ON CRIME RATES: OLS RESULTS

OLS Estimates	County-Level		CBSA-Level	
	Unbalanced Panel	Balanced Panel	Unbalanced Panel	Balanced Panel
	(1)	(2)	(3)	(4)
DEPENDENT VARIABLES: *Crime Rates per 1,000 residents*				
Violent Crime	**-0.002^{*} (0.001)**	**-0.003^{*} (0.001)**	**-0.002^{*} (0.001)**	**$-0.002^{\dagger}$ (0.001)**
Criminal Homicide	$-7.98e^{-7}$ ($5.64e^{-5}$)	$-4.75e^{-5}$ ($4.78e^{-5}$)	$-1.14e^{-4}$ ($7.50e^{-5}$)	$-9.96e^{-5}$ ($7.20e^{-5}$)
Forcible Rape	$-2.05e^{-4}$ ($1.43e^{-4}$)	$-2.64e^{-4}$ ($1.80e^{-4}$)	$-2.25e^{-4}$ ($1.94e^{-4}$)	$-2.47e^{-4}$ (1.95^{-4})
Robbery	$-1.83e^{-4}$ ($1.48e^{-4}$)	$-1.23e^{-4}$ ($1.73e^{-4}$)	**$-6.75e^{-4*}$ ($2.76e^{-4}$)**	**$-6.52e^{-4*}$ ($2.76e^{-4}$)**
Aggravated Assault	**$-0.002^{\dagger}$ (0.001)**	**$-0.002^{\dagger}$ (0.001)**	-0.001 (0.001)	-0.001 (0.001)
Property Crime	$-3.22e^{-5}$ (0.006)	0.002 (0.006)	-0.003 (0.01)	-0.004 (0.01)
Burglary	$6.98e^{-5}$ (0.001)	$6.99e^{-4}$ (0.002)	$9.86e^{-4}$ (0.003)	$-7.04e^{-5}$ ($2.65e^{-5}$)
Larceny Theft	$2.21e^{-4}$ (0.004)	$4.40e^{-4}$ (0.005)	-0.002 (0.008)	-0.003 (0.008)
Motor Vehicle Theft	$-3.46e^{-4}$ (0.001)	$7.79e^{-4}$ ($8.63e^{-4}$)	$5.10e^{-5}$ ($8.84e^{-4}$)	$1.45e^{-5}$ ($8.66e^{-4}$)
Arson	$2.27e^{-5}$ ($1.13e^{-4}$)	$1.09e^{-4}$ ($1.30e^{-4}$)	$-6.46e^{-5}$ ($1.87e^{-4}$)	$-2.71e^{-5}$ ($1.97e^{-4}$)
# Observations	23,537	22,328	7,790	7,419

Note: † p<0.10, *****p<0.05, ******p<0.01, *******p<0.001; Standard errors in parentheses are clustered at the state level.

TABLE 3.3 ESTIMATED EFFECT OF THE SUD TREATMENT RATE ON CRIME RATES: TSLS RESULTS

TSLS Estimates	County-Level				CBSA-Level			
	Unbalanced Panel		Balanced Panel		Unbalanced Panel		Balanced Panel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEPENDENT VARIABLES: *Crime Rates per 1,000 residents*								
Violent Crime Rates	**-0.14† (0.07)**	**-0.13* (0.07)**	**-0.24* (0.11)**	**-0.21* (0.10)**	-0.11 (0.09)	**-0.09† (0.05)**	**-0.14* (0.05)**	**-0.12* (0.04)**
Criminal Homicide	0.0002 (0.001)	0.001 (0.001)	0.0006 (0.001)	0.001 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Forcible Rape	0.01 (0.06)	-0.01 (0.04)	-0.005 (0.05)	-0.02 (0.03)	0.01 (0.06)	0.006 (0.04)	**-0.02† (0.01)**	-0.02 (0.01)
Robbery	**-0.03† (0.02)**	**-0.03* (0.02)**	**-0.04† (0.02)**	**-0.03† (0.02)**	**-0.03* (0.01)**	**-0.03* (0.01)**	**-0.02* (0.01)**	**-0.02* (0.01)**
Aggravated Assault	**-0.12* (0.05)**	**-0.10† (0.05)**	**-0.18* (0.09)**	**-0.16† (0.09)**	**-0.08† (0.05)**	-0.06 (0.04)	**-0.08* (0.04)**	**-0.07* (0.04)**
Property Crime Rates	**-0.67* (0.32)**	**-0.72† (0.41)**	**-0.67* (0.31)**	**-0.71† (0.42)**	-0.52 (0.34)	**-0.58† (0.35)**	-0.42 (0.36)	**-0.43† (0.26)**
Burglary	-0.05 (0.08)	-0.07 (0.09)	-0.05 (0.11)	-0.07 (0.10)	-0.03 (0.06)	-0.05 (0.07)	-0.01 (0.05)	-0.04 (0.06)
Larceny Theft	**-0.50† (0.28)**	**-0.55* (0.30)**	-0.52 (0.33)	**-0.54† (0.34)**	**-0.43† (0.26)**	**-0.46† (0.27)**	-0.38 (0.24)	**-0.36† (0.22)**
Motor Vehicle Theft	-0.13 (0.09)	**-0.11† (0.06)**	-0.10 (0.06)	-0.11 (0.07)	-0.06 (0.06)	-0.07 (0.05)	-0.02 (0.03)	-0.04 (0.03)
Arson	0.001 (0.005)	-0.0004 (0.01)	0.004 (0.003)	-0.001 (0.01)	-0.004 (0.005)	-0.005 (0.006)	-0.0006 (0.002)	-0.002 (0.004)
INSTRUMENTS: (Stage-I Dependent Variable: *SUD Treatment Rate per 1,000 residents*)								
HIFA (0/1)	**2.67*** (0.41)**	**2.60*** (0.35)**	**2.57*** (0.52)**	**2.50*** (0.47)**	**3.96** (1.26)**	**3.93** (1.21)**	**4.36** (1.41)**	**4.32** (1.38)**
Parity (0/1)		**0.91* (0.42)**		**0.86* (0.45)**		**1.47* (0.72)**		**1.39* (0.65)**
# Observations	23,537	23,537	22,328	22,328	7,790	7,790	7,419	7,419
F-statistic ‡	42.0	29.5	24.6	14.6	14.1	9.4	17.6	10.8

Note: † $p<0.10$, *$p<0.05$, **$p<0.01$, ***$p<0.001$; Standard errors in parentheses are clustered at the state level;
‡ Stock-Yogo (2005) weak identification test critical values based on maximal TSLS size of a 5% Wald test of $\beta = \beta_0$ (size test): K1=1 & L1=1: 10%: 16.38; 15%: 8.96; 20%: 6.66; 25%: 5.53; K1=1 & L1=2: 10%: 19.93; 15%: 11.59; 20%: 8.75; 25%: 7.25.

TABLE 3.4 ESTIMATED EFFECTS OF PAST & FUTURE POLICY CHANGES ON THE SUD TREATMENT RATE & CRIME RATES,

CHECKS FOR POLICY ENDOGENEITY

LPM Estimates	County-Level Unbalanced Panel				County-Level Balanced Panel			
	SUD Treatment Rate		*Total Crime Rate*		*SUD Treatment Rate*		*Total Crime Rate*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POLICY LAGS & LEADS:								
HIFA (0/1)	**2.43*** (0.41)**		**-0.11† (0.08)**		**2.44*** (0.52)**		**-0.14** (0.05)**	
2-Year Before T_{HIFA}		-0.33 (0.72)		0.02 (0.02)		-0.32 (0.72)		0.02 (0.02)
1-Year Before T_{HIFA}		-0.43 (0.67)		0.01 (0.02)		-0.43 (0.67)		0.02 (0.02)
Year of T_{HIFA}		**2.05* (1.01)**		-0.07 (0.07)		**2.06* (0.98)**		-0.10 (0.08)
1-Year After T_{HIFA}		**2.62*** (0.52)**		**-0.12† (0.07)**		**2.64** (0.67)**		**-0.12* (0.05)**
2-Year After T_{HIFA}		**1.59† (0.95)**		**-0.08† (0.05)**		1.06 (0.86)		**-0.07† (0.04)**
Parity (0/1)	**0.96* (0.43)**		-0.04 (0.03)		**0.87* (0.44)**		-0.03 (0.02)	
2-Year Before T_{Parity}		0.14 (0.53)		-0.008 (0.03)		0.14 (0.53)		-0.01 (0.03)
1-Year Before T_{Parity}		-0.07 (0.43)		0.01 (0.07)		-0.07 (0.43)		0.01 (0.07)
Year of T_{Parity}		**0.98* (0.48)**		-0.02 (0.02)		**0.98* (0.48)**		-0.01 (0.01)
1-Year After T_{Parity}		0.55 (0.34)		**-0.02† (0.01)**		0.55 (0.34)		**-0.02† (0.01)**
2-Year After T_{Parity}		0.56 (0.35)		-0.006 (0.004)		0.56 (0.35)		-0.007 (0.006)
# Observations	23,537	23,537	23,537	23,537	22,328	22,328	22,328	22,328

Note: † p<0.10, *****p<0.05, ******p<0.01, *******p<0.001; Standard errors in parentheses are clustered at the state level;
‡ T_{HIFA} and T_{Parity} indicate the first full year after the effective time of HIFA-waiver expansion and SUD parity mandate, respectively.

TABLE 3.5 ESTIMATED EFFECT OF THE SUD TREATMENT RATE ON CRIME RATES, ADDING STATE-SPECIFIC LINEAR TRENDS

TSLS Estimates	County-Level				CBSA-Level			
	Unbalanced Panel		Balanced Panel		Unbalanced Panel		Balanced Panel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEPENDENT VARIABLES: *Crime Rates per 1,000 residents*								
Violent Crime Rates	-0.15 (0.14)	-0.13 (0.11)	**-0.16*** **(0.08)**	**-0.15**† **(0.08)**	-0.18 (0.20)	-0.13 (0.21)	-0.22 (0.19)	-0.15 (0.14)
Criminal Homicide	-0.002 (0.002)	-0.002 (0.002)	-0.0005 (0.001)	-0.0008 (0.001)	-0.008 (0.007)	-0.003 (0.002)	-0.007 (0.007)	-0.003 (0.003)
Forcible Rape	0.01 (0.05)	0.01 (0.04)	0.008 (0.05)	0.005 (0.04)	0.02 (0.08)	-0.002 (0.04)	-0.003 (0.02)	-0.004 (0.03)
Robbery	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	**-0.02**† **(0.01)**	-0.03 (0.02)	-0.01 (0.01)	-0.05 (0.03)	-0.02 (0.01)
Aggravated Assault	-0.15 (0.14)	-0.17 (0.12)	**-0.15*** **(0.07)**	**-0.14**† **(0.08)**	-0.19 (0.12)	-0.10 (0.12)	-0.13 (0.10)	-0.09 (0.08)
Property Crime Rates	-0.67 (0.48)	-0.77 (0.52)	**-0.76**† **(0.39)**	**-0.86*** **(0.39)**	-0.78 (0.58)	-0.80 (0.56)	-0.83 (0.55)	**-0.82**† **(0.47)**
Burglary	**-0.23**† **(0.13)**	**-0.24**† **(0.13)**	**-0.24*** **(0.11)**	**-0.26*** **(0.12)**	-0.26 (0.18)	-0.20 (0.14)	**-0.27**† **(0.16)**	-0.23 (0.21)
Larceny Theft	-0.36 (0.31)	-0.42 (0.34)	**-0.44**† **(0.25)**	**-0.49**† **(0.26)**	-0.39 (0.24)	**-0.44**† **(0.24)**	-0.41 (0.32)	**-0.43**† **(0.23)**
Motor Vehicle Theft	-0.07 (0.05)	-0.10 (0.06)	-0.07 (0.04)	**-0.11*** **(0.06)**	-0.14 (0.11)	**-0.15**† **(0.07)**	-0.16 (0.14)	**-0.16*** **(0.08)**
Arson	-0.003 (0.004)	-0.005 (0.006)	-0.007 (0.004)	-0.01 (0.008)	-0.01 (0.01)	-0.006 (0.006)	-0.009 (0.009)	-0.005 (0.006)
INSTRUMENTS: (Stage-I Dependent Variable: *SUD Treatment Rate per 1,000 residents*)								
HIFA (0/1)	**3.99**** **(1.50)**	**3.95*** **(1.62)**	**3.52**** **(1.06)**	**3.50**** **(1.07)**	**2.58**** **(1.26)**	**2.47*** **(1.17)**	**2.90*** **(1.29)**	**2.77*** **(1.14)**
Parity (0/1)		0.50 (0.98)		0.48 (0.82)		**2.03**† **(1.12)**		**2.00**† **(1.05)**
# Observations	23,537	23,537	22,328	22,328	7,790	7,790	7,419	7,419
F-statistic ‡	8.9	4.6	11.1	5.6	4.3	3.1	5.5	3.5

Note: † p<0.10, *****p<0.05, ******p<0.01, *******p<0.001; Standard errors in parentheses are clustered at the state level;
‡ Stock-Yogo (2005) weak identification test critical values based on maximal TSLS size of a 5% Wald test of $\beta = \beta_0$ (size test).

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CHAPTER 4:
The Effect of Medical Marijuana Laws on Adolescent and Adult Use of Marijuana, Alcohol, and Other Substances

We estimate the effect of medical marijuana laws (MMLs) in ten states between 2004 and 2012 on adolescent and adult use of marijuana, alcohol, and other psychoactive substances. We find increases in the probability of current marijuana use, regular marijuana use and marijuana abuse/dependence among those aged 21 or above. We also find an increase in marijuana use initiation among those aged 12-20. For those aged 21 or above, MMLs further increase the frequency of binge drinking. MMLs have no discernible impact on drinking behavior for those aged 12-20, or the use of other psychoactive substances in either age group.

* A published journal article of this study is available:
http://www.sciencedirect.com/science/article/pii/S0167629615000351
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The authors declare that they have no relevant or material financial interests that relate to the research described in this study. The study was approved by the Emory University Institutional Review Board (IRB) through an expedited review procedure.

4.1 Introduction

As of February, 2015, 23 states and the District of Columbia have implemented medical marijuana laws (MMLs), which permit marijuana use for medical purposes. Three states (i.e., Maryland, Minnesota, and New York) adopted MMLs during 2014, and an additional 11 states[39] passed pro-medical marijuana legislation. Medical marijuana bills have also been considered in many of the remaining states and are likely to land on the legislative agenda in more states in the near future. Understanding the behavioral and public health implications of this evolving regulatory environment is critical for the ongoing implementation of MMLs and future iterations of marijuana policy reform. Despite the growing consensus about the relief medical marijuana can bring for a range of serious illnesses, concerns have been voiced that MMLs may give rise to increased marijuana use in the general population and increased use of other substances. Legislative and public attention have focused on these issues, but the empirical evidence is limited.

We contribute to the literature on the effects of marijuana liberalization policies by examining the effect of the implementation of MMLs in ten states between 2004 and 2012 on a variety of substance use outcomes including marijuana use, alcohol use, pain medication misuse, and hard drug use in both adolescent and adult populations. To tease out the potential causal effect of MML implementation, we exploited the geographic identifiers in a restricted-access version of the National Survey on Drug Use and Health

[39] 11 states with pro-medical marijuana legislation include Alabama, Florida, Iowa, Kentucky, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Utah, and Wisconsin.

(NSDUH) micro-level data and estimated two-way fixed effects models with state-specific linear time trends and a rich set of individual- and state-level covariates.

We find that implementation of an MML leads to a relative 14 percent increase in the probability of past-month marijuana use and a 15 percent increase in the probability of almost daily/daily marijuana use among adults aged 21 or above. For this age group, MML implementation also results in a 10 percent increase in the probability of marijuana abuse/dependence. Among adolescents and young adults aged 12-20, we find a 5 percent increase in the probability of past-year marijuana use initiation attributable to MML implementation.

In addition to the increases in marijuana use, implementation of an MML also increases the frequency of binge drinking among those aged 21 or above, partially through increasing simultaneous use of the two substances. In contrast, MML implementation does not affect underage drinking among those aged 12-20. In both age groups, non-medical use of prescription pain medication, heroin use, and cocaine use are unaffected.

Overall, our findings indicate that state implementation of an MML increases marijuana use, but has limited impacts on other types of substance use (i.e., underage drinking, pain medication misuse, and hard drug use), except for binge drinking among adults of legal drinking age.

The article proceeds as follows. Section 4.2 provides background information on medical marijuana and MMLs, outlines the theoretical framework, and summarizes the existing literature. Section 4.3 describes the data sources, variable measurement, and identification strategy. Section 4.4 presents the estimated policy effects, and the robustness checks. Concluding remarks are given in the last section (Section 4.5) of the chapter.

4.2 Background

4.2.1 Medical Marijuana Law and Potential Risks and Medical Value of Marijuana

In the last two decades, growing evidence has lent support to the efficacy and safety of marijuana as medical therapy to alleviate symptoms and treat diseases (See, for instance, Ben Amar, 2006; Campbell and Gowran, 2007; Krishnan, Cairns, Howard, 2009; Pertwee, 2012; and Gloss and Vickrey, 2012). This growing body of clinical evidence on marijuana's medicinal value has propelled many states toward a more tolerant legal approach to medical marijuana. In 1996, California signed the Compassionate Use Act into law (Proposition 215) and became the first state in the U.S. to permit the medical use of marijuana. And since then a total of 23 states and the District of Columbia have passed MMLs. These laws are intended to protect patients from state prosecution for their medical marijuana use (Hoffmann and Weber, 2010).[40]

Typically under an MML, a patient with an eligible condition should first obtain recommendation from a qualified doctor for the use of marijuana in medical treatment. With

[40] In contrast to the state MMLs, federal law continues to prohibit marijuana use for any purpose since the enactment of the Controlled Substances Act (CSA) of 1970. A 2005 Supreme Court decision (Gonzales v. Raich) reaffirmed that federal law enforcement has the authority to prosecute patients for medical marijuana use in accordance with state laws (Gostin, 2005). It is only recently that the Obama administration and the Department of Justice clarified the position that federal law enforcement resources should not be dedicated to prosecuting persons whose actions comply with their states' permission of medical marijuana (Hoffmann and Weber, 2010). This change in the prosecutorial stance would strengthen the legitimacy of existing MMLs and pave the way for the passage of new MMLs.

the doctor's recommendation for medical marijuana use, the patient can then be issued a medical marijuana patient identification card by the state. The patient ID cardholder and his/her caregivers are allowed to possess a certain amount of marijuana through cultivation at home and/or purchase from a nonprofit retail dispensary licensed by the state (in some states called "compassionate center").[41] As such, MMLs in principle should only provide restricted legal protection and access to marijuana for a select group of patients. In practice however, the laws may have a spillover effect on marijuana use in the non-patient population.

The spillover effect may arise from four dimensions of the existing MMLs that create a de facto legalized environment for marijuana use in the general population (Pacula, et al., 2013). First, although all MMLs specify a list of conditions that are eligible for medical marijuana[42], most MMLs include in the list a generic term "chronic pain", rather than specific diseases causing the pain (e.g., neuropathy, fibromyalgia, rheumatoid arthritis, etc.) (Pacula, et al., 2013). The interpretation of "chronic pain" can go far beyond the original legislative intent, analogous to the practice of off-label prescribing of other medications. Because pain can often be non-descript and difficult to verify clinically, a recreational user may pretend to be a pain patient in order to obtain a prescription for medical marijuana.

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[41]Several more recent MMLs have taken innovative twists that are intended to tighten the regulation on access to medical marijuana. For instance, New York's 2014 MML is the first in the U.S. to allow doctors in qualified hospitals to *prescribe* medical marijuana instead of recommending it. By allowing for medical marijuana prescription, the law in effect imposes more responsibility on the participating doctors for certifying patients' medical need, as a doctor can be charged with a felony for prescribing marijuana to an ineligible patient.

[42]California is the only exception that allows medical marijuana for any condition "for which marijuana provides relief" and leaves the interpretation almost entirely to the discretion of doctors.

Second, some MMLs do not require establishment of a registry/renewal system to assess and monitor patient eligibility for medical marijuana. This, coupled with the loosely-defined eligibility criteria, further blurs the boundary between the patient and the non-patient population (Cohen, 2010).

Third, MMLs provide medical marijuana patients with access to the drug by allowing licensed retail dispensaries and/or home cultivation. These supply channels exist in a legal grey area and may proliferate as a result of the reduced threat of prosecution under the MMLs (Pacula, et al., 2014). In particular, Andersen, Hansen, and Rees (2013) provided empirical evidence that MMLs have led to a substantial increase in the supply of high-grade marijuana. As marijuana supply rises, it may become prohibitively expensive for law enforcement to ensure that the entire supply of marijuana intended for medical purpose ends up in the hands of legitimate patients, akin to how prescription opioids eventually find their way into the street drug market. This spillover to the non-patient population is likely to occur in places where marijuana possession is decriminalized, prosecution of a marijuana offense is local law enforcement's "lowest priority", and federal interference in marijuana regulation is limited (Sekhon, 2009).

In addition to those specific components of the law, an MML as a whole symbolizes liberalization of marijuana policy, which in turn, may give rise to the underestimation of the risks associated with marijuana use and the normalization of marijuana use for recreational purposes (Hathaway, Comeau, and Erickson, 2011).

4.2.2 Literature on the Effect of MML on Marijuana Use in the General Population

Empirical evidence is inconclusive with respect to the effect of an MML on marijuana use in the general population. A review of this line of literature is beyond the scope of our paper. We direct readers to Chu (2014) for a comprehensive review. Briefly, however, we note that the mixed findings from the previous studies can be explained by the heterogeneity between different age groups examined and the variation in specific state laws covered by the studies.

Studies on youths generally find no significant effect of an MML on youth marijuana use (e.g., Harper, Strumpf, and Kaufman, 2012; Lynne-Landsman, Livingston, and Wagenaar, 2013; Anderson, Hansen, and Rees, 2014). The most comprehensive evidence comes from Anderson, Hansen, and Rees (2014), which brings together several commonly used data sets and covers an 18-year period from 1993 to 2011. The study findings suggest that implementing an MML does not lead to a significant increase in marijuana use among youths. Compared to the literature on youth marijuana use, the existing literature on the adult population is relatively thin and limited in scope and rigor (e.g., Harper, Strumpf, and Kaufman, 2012; Andersen, Hansen, and Rees, 2011).

In addition to the potential heterogeneity in the response to an MML across age groups, MMLs may not be treated as a homogenous set of laws between states and across time. The variation in specific states laws implemented during different periods may help reconcile the mixed findings from the previous studies. To explore this potential heterogeneity, a recent study by Pacula et al. (2013) uses the same data sets as Anderson, Hansen, and Rees (2014) but replaces a single dichotomous MML indicator with a set of indicators that represent key provisions of MMLs. Although none of the estimates using a dichotomous MML indicator are significant, the MMLs that include a provision requiring patient registry/renewal are found to lower the marijuana use rates and marijuana-related treatment admissions. This protective effect of the patient registry/renewal requirement, however, is offset by another provision of MMLs that allows licensed retailors to dispense marijuana to medical marijuana patients. The third MML provision this study examines, the home cultivation provision, has inconsistent and sometimes counterintuitive effects on marijuana use. These study findings are informative as to the importance of distinguishing between MML provisions and recognizing the variation in state MMLs. A caveat, however, is that although Pacula et al. (2013) take a more nuanced approach to the classification of MMLs, they lump youths and adults together in their full-sample analysis. As a result, the aforementioned age heterogeneity may be obscured.

4.2.3 Spillover from Marijuana Use to the Use of Alcohol and Other Substances

On top of the spillover of marijuana use from medical marijuana patients to the non-patient population, the potential interdependence of substance use may lead to a further spillover from marijuana use to the use of other psychoactive substances.[43] Assuming marijuana has a downward sloping demand curve, the effect of an MML on marijuana use should be unequivocally positive. The effect on other substance use, however, can be positive or negative, depending on the relative magnitude of the income and substitution effects (Chaloupka and

[43]However, if the increased marijuana use arising from an MML is not for recreational purpose (i.e., “intoxication”) but for medical purpose only, the use of other substances is unlikely to be affected.

Laixuthai, 1997; Pacula, 1998). Specifically, contemporaneous substitution of marijuana for another substance in response to the implementation of an MML is most likely to occur for substances that have pharmacological effects most similar to that of marijuana. A complementary relationship, on the other hand, is most likely to occur between marijuana and another substance if their combined use produces a synergistic interaction (Moore, 2010). In addition to the contemporaneous relationship between marijuana use and other substance use, there may also be a progression from the demand for marijuana to the craving and thus future demand for a more powerful substance with more intense and longer-lasting effects (Kandel, 1975; Kandel, 2002).

Relationship between Marijuana Use and Alcohol Use: Marijuana and alcohol target many common neural pathways in human brains (Maldonado, Valverde, and Berrendero, 2006). On the one hand, marijuana use produces rewarding and sedative effects that are comparable to the effect of alcohol use (Boys, Marsden, and Strang, 2001; Heishman, Arasteh, and Stitzer, 1997), especially low-dose alcohol consumption[44] (King, et al., 2011). In this case, when MML lowers the cost of marijuana use, an individual may substitute marijuana for alcohol to achieve a similar experience such as a general sense of well-being, with perhaps fewer immediate negative physical symptoms (e.g. hangovers).

On the other hand, the overall intoxication experience may be enhanced by the simultaneous use of marijuana and alcohol together. Evidence suggests that ethanol,

[44]High-dose alcohol consumption, in contrast, tends to lower sedation and heighten stimulation (King, et al., 2011).

especially when consumed in high doses, can facilitate the absorption of delta 9-tetrahydrocannabinol (THC) (Boys, Marsden, and Strang, 2001). In a randomized control trial (RCT) conducted by Lukas and Orozco (2001), participants reported significantly more episodes and longer durations of euphoria when consuming marijuana together with high doses of alcohol. The enhanced euphoria following simultaneous consumption of alcohol and marijuana may subsequently lead to a greater urge to drink even more. Such a scenario points toward a competing hypothesis that marijuana and alcohol, especially high-dose alcohol consumption, are complements rather than substitutes. In this case, an MML may result in the increased use of both substances.

The takeaway of these pharmacologic findings is that whether marijuana and alcohol are substitutes or complements may depend on individual motives for substance use. For instance, those who only expect a mild feeling of happiness and relaxation from substance use may consume one of the substances in place of the other. In contrast, those seeking intense euphoria would consume the two substances together, perhaps in higher doses.

Relationship between Marijuana Use and Other Substance Use: Marijuana is also widely portrayed as a “gateway” drug, essentially inducing the use of drugs with more serious health, legal and social consequences (Kandel, 1975; Kandel, 2002). One hypothesized pathway is through pharmacological mechanisms: once users tolerate the psychoactive effects of marijuana use, they may crave and seek out more powerful drugs with more intense and longer-lasting effects. This pharmacological mechanism would thus predict an increase in subsequent use of hard drugs such as heroin and cocaine attributable to the implementation of an MML.

An alternative to this pharmacological mechanism is that the observed sequence from marijuana use to hard drug use may simply reflect common predisposing factors rooted in genes or in the environment coupled with an exposure opportunity mechanism through which marijuana users may be introduced to a shared market or subculture of hard drugs (Morral, et al., 2002; Wagner and Anthony, 2002a). If predisposing factors and exposure opportunities are the primary mechanisms that lead users to transition from marijuana use to hard drug use, an MML should not result in an increase in hard drug use because the predisposing factors and exposure opportunities[45] for hard drug use remain unaffected.

In contrast to the concern about MML's "gateway" effect, there has been evidence that increased access to medical marijuana resulting from an MML may benefit certain individuals by reducing their opioid use. For instance, marijuana may provide analgesia for patients with chronic pain (Lynch and Campbell, 2011). Thus, those who have already received opioid pain medication may experience improved pain relief and lower their opioid dose after they commence medical marijuana treatment. In addition, those who would have otherwise initiated opioid analgesics may choose medical marijuana instead (Abrams, 2011). Furthermore, marijuana may also benefit those with opioid misuse (i.e., non-medical use) by easing

[45]The existing MMLs help marijuana users gain access to the drug through medical marijuana dispensaries and home cultivation, which are unlikely to expose the marijuana users to the market or subculture of hard drugs.

withdrawal symptoms and facilitating recovery (Scavone, Sterling and Van Bockstaele, 2013). Therefore, one would expect states with MMLs to see a reduction in prevalence of opioid use, or other downstream benefits such as reduced overdose mortality (Bohnert, et al., 2011; Bachhuber, et al., 2014).

4.2.4 Literature on the Relationship between Marijuana Use & the Other Substance Use

Through increased marijuana use, a further consequence of an MML could also be the spillover to alcohol use and the use of other psychoactive substances. Identification of the spillover effect in an observational study hinges on the isolation of the exogenous variation in substance use arising from policy/price shocks from the endogenous variation due to "common factors" or "exposure opportunities."

Previous studies have exploited changes in state excise taxes on beer (Pacula, 1998), the minimum legal drinking age (MLDA) (DiNardo and Lemieux, 2001; Yörük and Yörük, 2011, 2012; Crost and Guerrero, 2012) composite market prices of alcohol (Saffer and Chaloupka, 1999) and market prices of cocaine (Saffer and Chaloupka, 1999; DeSimone and Farrelly, 2003) to tease out the exogenous changes in the use of alcohol or cocaine as well as the downstream use of marijuana. Although they generally find a direct policy/price effect on the use of the target substance itself (e.g., alcohol and cocaine) that follows a downward sloping demand curve, the downstream effect on marijuana use is mixed. Chaloupka and Laixuthai (1997), DiNardo and Lemieux (2001), Crost and Guerrero (2012), and Crost and Rees (2013) find evidence for a substitution between marijuana and alcohol. However, Pacula (1998), Saffer and Chaloupka (1999), and Yörük and Yörük (2011) find evidence supporting the complementarity hypothesis between marijuana and alcohol. Moreover, evidence from Saffer and Chaloupka (1999) and DeSimone and Farrelly (2003) suggests a complementarity between marijuana and cocaine.

Not only is there a lack of consistent evidence, it is also difficult to extrapolate the effect of an MML on the use of other substances from the estimated reduced-form effect of policy/price related to the other substances on the use of marijuana. This difficulty arises out of the nature of the underlying Marshallian demand function, which does not require symmetric relationships between substances (i.e., from substance A to B vs. from substance B to A), nor does it require symmetric responses to policy/price changes (i.e., permissive policy/lower price vs. restrictive policy/higher price). Thus it is possible for marijuana to be a substitute for alcohol when alcohol regulations become more restrictive but for alcohol be a complement to marijuana when marijuana policies become more permissive.[46]

Within the context of MMLs, Anderson, Hansen, and Rees (2013) provide evidence that states with MMLs see a reduction in alcohol-related traffic fatalities, alcohol consumption and beer sales. However, the authors do not have data on changes in marijuana use, thus their findings do not necessarily imply that marijuana is a substitute for (or a complement to) alcohol. In fact, when taking into account the key provisions of MMLs, the replication study by Pacula et al. (2013) suggests that the findings from traffic

[46]This asymmetric relationship between marijuana use and alcohol use may come into play in the context of the minimum legal drinking age (MLDA) vs. an MML: a teenager under the MLDA cannot legally acquire either alcohol or marijuana and may resort to illegal supply channels, whereas an experienced marijuana user living in a MML state can get both marijuana and alcohol with little effort. In essence, when identifying the relationship between marijuana and alcohol, using different policies may capture the decisions made by different groups from different choices set. Thus, the results from one policy may not applicable to another policy setting.

fatalities and alcohol consumption are more consistent with a complementarity hypothesis. Nonetheless, the authors are only able to assess two outcomes related to alcohol consumption, which limits the scope of their study.[47]

Another piece of evidence in the context of MMLs comes from Bachhuber, et al. (2014), which assesses the mortality rate related to opioid overdose. The authors find a 25 percent reduction in the annual rate of opioid overdose mortality between 1999 and 2010 in states with MMLs compared to those without such laws. However, the unaccounted state heterogeneity in the underlying prevalence of opioid use or trajectory of overdose deaths may also contribute to the reduced mortality rate. Therefore, the reduction in opioid overdose mortality rate may not necessarily imply a substitution between marijuana and opioids.

In sum, the majority of the literature on the relationship between marijuana use and the use of alcohol and other substances relies on policy/price shocks other than MMLs for identification. Evidence from this line of literature is inconsistent and may not extrapolate to the effect of an MML. Existing literature in the context of MML, however, is relatively thin and limited in scope and rigor.

4.2.5 Significance of Our Study

[47]The first outcome in Pacula et al. (2013), any current alcohol use, may not carry as much weight as binge or heavy drinking in terms of health consequences and policy implications, especially for adults of legal drinking age. The other outcome, specialty alcohol abuse treatment admissions, may not show a clear picture of the alcohol abuse/dependence prevalence, since more than 90 percent of Americans who suffer from alcohol abuse/dependence do not receive any treatment for their conditions. Furthermore, a large proportion of those receiving the treatment only receive it in a self-help group (e.g., Alcoholics Anonymous) or in a primary care setting as opposed to a specialty alcohol abuse treatment setting (SAMHSA 2013).

To inform the current debate on MMLs and marijuana liberalization policies in general, we examine the effect of state implementation of MMLs between 2004 and 2012 on marijuana use, alcohol use, pain medication misuse, and hard drug use in both adolescent and adult populations. Our study advances the existing literature by: (i) providing one of the first estimates of the effect of MML implementation on adult marijuana use based on micro-level nationally-representative data, as well as the updated estimates for adolescent marijuana use based on the most recent data; (ii) estimating the effect of MML implementation on a variety of substance use outcomes with differential elasticities and expected harms; (iii) estimating the contemporaneous relationship between marijuana and alcohol and other substances within the context of MMLs; (iv) estimating explicitly the heterogeneous policy effects of key MML provisions between different age groups.

4.3 Methods

4.3.1 Data Sources

We pooled nine years of cross-sectional data from a restricted-access version of the National Survey on Drug Use and Health (NSDUH) 2004-2012 (CBHSQ, 2013). NSDUH is a nationally and state-representative[48] survey sponsored by the Substance Abuse and Mental Health Services Administration (SAMHSA), and the primary source of information

[48]The NSDUH sampling frame is state-based, with an independent, multistage area probability sample within each state and the District of Columbia. The eight states with the largest population (i.e., California, Florida, Illinois, Michigan, New York, Ohio, Pennsylvania, and Texas) have an annual sample size of about 3,600 each. For the remaining 42 states and the District of Columbia, each has a sample size of about 900 annually.

on substance use behavior by the U.S. civilian, noninstitutionalized[49] population aged 12 or above. The majority of the NSDUH interview is conducted by self-administrated audio computer-assisted self-interviewing (ACASI), a highly private and confidential mode that encourages honest reporting of substance use and other sensitive behaviors (Johnson, Fendrich, and Mackesy-Amiti, 2010). The response rates range from 73 percent to 76 percent between 2004 and 2012.

4.3.2 Variable Measurement

Marijuana Use Outcomes: We created five outcomes related to marijuana use: (i) a dichotomous indicator assessing whether a respondent used marijuana during the past month prior to the interview; (ii) another dichotomous indicator assessing whether a respondent used marijuana “almost daily or daily”, defined as more than 20 days of marijuana use during the past month; (iii) the number of marijuana use days among past-month marijuana users, which is an conditional frequency ranging from 1 to 30;[50] (iv) a dichotomous indicator for using marijuana for the first time during the past year;[51] and (v) a dichotomous indicator for being classified as abusing or being dependent on marijuana during the past year according to DSM-IV diagnostic criteria. The DSM-IV defines past-

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[49]Institutionalized individuals (e.g. in jails/prisons or hospitals), homeless or transient persons not in shelters, and military personnel on active duty were excluded from the NSDUH sample.

[50] The majority of past-month marijuana users either use marijuana on a few occasions or use it regularly, with a very small proportion of marijuana users between these two extremes. Therefore, we assessed both the average change in the frequency of marijuana use days and the change in the right tail of the frequency distribution (i.e., almost daily/daily marijuana use).

[51]Marijuana use initiation is examined in an “at-risk” sample, which excludes those who first tried marijuana more than a year prior to the interview thus no longer at risk of *initiating* marijuana use during the preceding year.

year substance abuse/dependence as a maladaptive pattern of substance use leading to clinically significant impairment and distress during the past year. The impairment and distress related to substance use can be manifested by symptoms such as tolerance, withdrawal, use of a substance in a larger amount or over a longer period of time than intended, continued substance use in dangerous situations, interference with major obligations, etc. (APA, 2000). (Table 4.8)

Alcohol Use Outcomes: Empirical evidence suggests that marijuana can be a substitute for and a complement of alcohol, depending on individual motives of substance use and doses of consumption. Lower-dose alcohol consumption for mild happiness and relaxation is hypothesized to be replaced by marijuana use (King, et al., 2011), whereas higher-dose alcohol consumption for intense euphoria is hypothesized to be accompanied by marijuana use (Lukas and Orozco, 2001). In this regard, we studied any alcohol use as well as binge drinking.[52] Binge drinking, in the NSDUH, is defined as having five or more drinks on the same occasion on at least one day during the past month.[53] We created the following measures for alcohol use: (i) the total amount of drinks consumed during the past month,[54] (ii) the unconditional frequency of binge drinking days, and (iii) the probability of being

[52]Carpenter and Dobkin (2009), for instance, find evidence for the differential elasticity of alcohol demand along the distribution of drinking intensity and frequency.

[53]A commonly used alternative defines "binge drinking" as five or more drinks for men and four or more drinks for women consumed on one occasion (Wechsler, et al., 1995). Our estimates are robust to this gender-specific definition (not shown).

[54]One drink refers to a can or a bottle of beer, a glass of wine or a wine cooler, a shot of liquor, or a mixed drink with liquor in it.

classified as having alcohol abuse/dependence during the past year according to the DSM-IV criteria. We also created two dichotomous indicators to assess: (iv) whether a respondent engaged both in marijuana use and in binge drinking during the past month, and (v) whether a respondent used marijuana while drinking alcohol (i.e., on the same occasion) during the past month.[55] These two measure of simultaneous use of marijuana and alcohol can provide further insight into the contemporaneous complementarity between the two substances.

Other Substance Use Outcomes: In light of the previous evidence suggesting a substitution between marijuana and opioids (Bachhuber, et al., 2014) and a complementarity between marijuana and cocaine (Saffer and Chaloupka, 1999; DeSimone and Farrelly, 2003), we focused our analysis on non-medically used prescription pain medication,[56] heroin, and cocaine. NSDUH defines "non-medical use" as the intentional use of a medication without a prescription, in a way other than as prescribed, or simply for the experience or feeling that it causes. NSDUH does not include questions about legitimate pain medication used according to the prescription. We created three

[55]The question about simultaneous use of marijuana and alcohol is not included in the NSDUH 2004 and 2005 surveys, while the MMLs in Vermont and Montana both came into effective in 2004. Thus we cannot estimate the effect of these two states' implementation of the MMLs on this outcome.

[56]NSDUH attempts to capture all types of pain medication by including in its questionnaire a list of commonly prescribed and misused pain medications in their generic names (e.g., Codeine, Oxycodone, Hydrocodone, Morphine, Hydromorphone, Fentanyl, Tramadol, etc.), brand names (e.g., OxyContin, Vicodin, MSContin, Dilaudid, Duragestic, Ultram, etc.) and street names, along with an open-ended question about other pain medications.

dichotomous indicators for the probability of: (i) past-year non-medical use of prescription pain medication, (ii) past-year heroin use, and (iii) past-year cocaine use.

MML-Implementation Indicator: The recent launch of the Data Portal system by the CBHSQ provides us with access to state identifiers and interview dates in a restricted-access version of the NSDUH micro-level data, thus enabling us to create a dichotomous indicator for the implementation of a MML in a given state during a given period. As summarized in Table 4.1, between 2004 and 2012, MMLs came into effect in ten states at various time points. We assigned the MML-implementation indicator a value of 1 for each full month subsequent to the effective date of the laws, and a value of 0 for the remaining periods and for the control states.[57] Control states include eight states that had an MML in place prior to 2004 (i.e., “always MML states”) and those that did not have any MML by the end of 2012 (i.e., “no MML states”).[58]

In addition to examining the effect of implementation of an MML as a whole, Pacula, et al. (2013) recognizes the importance of scrutinizing the potential heterogeneous effects between individual components of an MML. As highlighted in their study, four key components that may be included in an MML and lead to heterogeneity in the policy effect

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[57]Note that most previous studies based on annual surveys were only able to estimate year-on-year policy effect. In our study, we linked the NSDUH interview dates with the MML effective dates and matched the month-to-month implementation window of the MMLs with the behavior window of the NSDUH respondents. This approach minimizes the potential measurement error from misclassification of pre-MML and post-MML behaviors.

[58]We also estimated two alternative model specifications: the first specification classifies the “always MML states” as the control states, whereas the second specification classifies the “no MML states” as the control states. The estimated policy effects on the main outcomes are very similar across the models (not shown).

are: (i) "non-specific pain" provision, which lists a generic "chronic pain" in the eligible conditions for medical marijuana, rather than specifying diseases causing the pain; (ii) "patient registry" provision, which requires a patient registry/renewal system; (iii) "retail dispensary" provision, which allows licensed marijuana retailors to dispense marijuana legally to medical marijuana patients; and (iv) "home cultivation" provision, which allows qualified patients and caregivers to grow a certain amount of marijuana plants indoors for the patients' own medical use. Accordingly, we created four indicators each representing the inclusion of a key MML provision. Note that for an MML state, the inclusion date of a MML provision may differ from the effective date of the MML, as the state may include the provision in the original statute, add it in a subsequent amendment, or not include it in the law until the end of the study period.

Covariates: We controlled for individual-level and state-level factors that are correlated with both the individual choice to use substances and with state decisions about MMLs. Individual-level covariates for adolescents and adults include a rich set of sociodemographic characteristics. State-level covariates include three time-varying measures reflecting the fluctuation in state economic conditions: (i) unemployment rate, (ii) average personal income, and (iii) median household income of the state, as well as two additional measures reflecting relevant changes in state policy environment. One major policy change during the study period concerns state implementation of beer taxes.[59] The other policy change is marijuana decriminalization/depenalization: Massachusetts, California, and several cities and counties in other states relaxed penalties for recreational marijuana use or placed it "the lowest law enforcement priority." We therefore created a dichotomous indicator for the implementation of a decriminalization/depenalization policy in a given state during a given month.[60] Table 4.2 provides descriptive summary for the individual-level and state-level covariates discussed above.

4.3.3 Identification Strategy

To identify the effect of MML implementation on individual marijuana use, alcohol use, pain medication misuse, and hard drug use, we estimated the following two-way fixed effects models:

$$\boldsymbol{Y_{ist}} = \beta_0 + \beta_1\, \boldsymbol{MML_{st}} + \beta_2\, \boldsymbol{X_{1\,ist}} + \beta_3\, \boldsymbol{X_{2\,st}} + \rho_s + \tau_t + \rho_s\, t + \varepsilon_{ist} \tag{1}$$

where i denotes an individual, s denotes the state, and t denotes the year. Y_{ist} represents the substance use outcomes. MML_{st} is the policy indicator for the implementation of an MML in a state s during a year t. X_{1ist} is the full vector of individual-level covariates. X_{2st} is the full vector of state-level covariates. The two-way fixed effects are captured in our

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[59]We did not control for the market price of heroin or cocaine. The most commonly used source is the U.S. Drug Enforcement Administration's System to Retrieve Information from Drug Evidence (STRIDE) dataset. Empirical studies often find that STRIDE prices are not predictive or only weakly predictive of drug use (Horowitz, 2001). As French and Popovici (2011) pointed out, "part of difficulty here is that conventional prices for illicit drug are not readily available and alternative measures are not yet found." Nonetheless, fluctuations in heroin prices and cocaine prices are unlikely to be correlated with the MML implementation, thus omitting these variables is unlikely to bias our results.

[60]For lack of policy variations during the study period, the effect of a decriminalization/depenalization policy itself cannot be precisely estimated.

models by ρ_s and τ_t to account for the time-invariant state heterogeneity as well as the national secular trend and common shocks related to substance use. We also included state-specific linear time trends $\rho_s t$ to account for the unobserved state-level factors that evolve over time at a constant rate (e.g., social norms and public sentiments related to substance use).

Standard errors were clustered at the state level to correct for the serial correlation. The clustered standard errors allow for arbitrary within-state correlation in error terms but assume independence across the states (Bertrand, et al., 2004).[61]

We stratified the sample into two age groups, adolescents and young adults aged 12-20 (N ≈ 269,500) and adults aged 21 or above (N ≈ 323,900). We chose age-21 as the cutoff point in light of the previous evidence of an age-21 discontinuity in both alcohol use and marijuana use (Crost and Guerrero, 2012; Yörük and Yörük, 2011, 2012). We tested four cut-off points in our analyses, age-18, age-21, age-25 and age-30. Only the age-21 stratification, which also coincides with the legal drinking age, produces significant and meaningful differences in the estimated policy effect between age groups.

[61] It is worth noting that NSDUH employs a multistage (stratified cluster) design for the sample selection. The sampling design elements include survey weights, variance estimation cluster replicates and variance estimation stratum. The descriptive statistics were adjusted for these survey design elements to make the analytic sample representative of the U.S. population. However in regression analysis, using the STATA "svy" procedure to adjust for the weighting, clustering, and stratification of the NSDUH sampling design would suppress the state-clustering adjustment. When considering the choice between the two, Solon, Haider and Wooldridge (2013) noted that theoretically "neither strictly dominates the other (in identifying the population average effect)" (Solon, Haider and Wooldridge, 2013, pp.21). Furthermore, in our study, the results from both the unweighted, state-clustering adjusted models and the weighted, sampling-design adjusted were similar (not shown). Therefore, we report the unweighted, state-clustering adjusted estimates.

We estimated Probit regressions for the dichotomous dependent variables in our study. The other three discrete dependent variables we study (i.e., the conditional frequency of marijuana use days, the number of alcohol drinks, and the unconditional frequency of binge drinking days) possess positive skewness and/or "excess zeroes" compared to a standard normal distribution, which requires a more flexible estimation approach than an ordinary least squares (OLS) estimation. A generalized linear model (GLM) with a gamma distribution and log link[62] was estimated for the total amount of drinks during the past month among those aged 21 or above. For the total amount of drinks among those aged 12-20, on the other hand, we estimated a two-part model using Probit in the first part and GLM (gamma distribution and log link) in the second part. Because there is an explicit decision process regarding legality of alcohol consumption among those under 21, we use the TPM to model the decision to engage in underage drinking and the quantity consumed conditional upon deciding to engage in underage drinking as separate processes. We followed the same logic when estimating the frequency variables. Considering the underlying decision processes and the proportions of zero values, we estimated a zero-truncated negative binomial regression[63] for the conditional frequency of marijuana use days and a zero-inflated negative binomial regression[64] for the unconditional frequency of binge drinking days in both age groups.

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[62]The selection of distribution family under the GLM was made based on the modified Park test results.

[63]The likelihood ratio test for overdispersion rejects a Poisson distribution in favor of a binomial distribution.

[64]The likelihood ratio tests for overdispersion reject a Poisson distribution in favor of a binomial distribution. Furthermore, the Vuong tests for zero-inflation confirm our choice of a zero-inflated model instead of an ordinary negative binomial model.

The zero-inflated Poisson/negative binomial model assumes that the sample consists of two distinct groups of people: one group whose counts are generated by the standard Poisson/negative binomial model, and the other group, so-called "absolute zero" group, who have zero probability of a count greater than zero; observed zeroes can come from either group (Greene, 2011; Wang, 2003). The absolute zero group, in our case, may be those who abstain from alcohol for

For ease of interpretation, we converted the coefficient of MML_{st} in each of the estimations to the average marginal effect calculated at $MML_{st} = 0$ and the observed values of other covariates.

4.4 Results

4.4.1 Estimated Effect of MML Implementation on Marijuana Use

Figure 1 shows an upward trend in past-month marijuana use rates among adults aged 21 or above in parallel with the implementation of MMLs. A relative increase in adult marijuana use in MML states emerges immediately after the laws take effect, and persists at least three years afterwards. Among adolescents and young adults aged 12-20, however, the corresponding trend in past-month marijuana use rates is not consistent. Bear in mind that the relative trends shown in Figure 1 are equivalent to unadjusted DD estimates that only partial out the two-way fixed effects (i.e., time-invariant state heterogeneity and national secular trend in past-month marijuana use), but do not adjust for the individual- and state-level covariates or state-specific linear trends. Nonetheless, this observational trend-comparison suggests a potential association between MML implementation and

religious, cultural, familial or other reasons. Thus, this group of people, as distinct from the majority of people who drink alcohol at least occasionally, have "absolute zero" risk of binge drinking.

An alternative to a zero-inflated regression is a hurdle model (i.e., a TPM for counts) with first-part Probit and second-part zero-truncated negative binomial. A practical challenge, however, is that cluster-adjusted standard errors are difficult to compute when combining the first- and second-part estimates from a hurdle model (Belotti, et al., 2014). Nonetheless, the point estimates for the combined effects we obtained from the hurdle models (not shown) were very similar to the zero-inflated negative binomial estimates from our main analyses. In another set of sensitivity analyses, we also treated the count variables as continuous and estimated the combined marginal effects and their cluster-adjusted standard errors using the STATA command "TPM" (Belotti, et al., 2014). The TPM estimates (not shown) were slightly larger and more significant than the zero-inflated negative binomial estimates.

increased current marijuana use among adults aged 21 or above, but not among adolescents and younger adults.

Table 4.3 presents the marginal effects of MML implementation on the four marijuana use outcomes, adjusted for the two-way fixed effects, the full vector of individual- and state-level covariates, and the state-specific linear trends. Among adults aged 21 or above, the implementation of an MML increases the probability of using marijuana during the past month by 1.32 percentage points (Panel B, Column 1, Row 1). This percentage point change can be translated into a 14 percent relative increase from a baseline predicted marijuana use probability of 9.33 percentage points.

The NSDUH data do not allow us to distinguish between medical marijuana patients and the non-patient population. Nonetheless, according to the registry data (Anderson, Hansen and Rees, 2013), the number of registered medical marijuana patients accounts for an average of 0.8 percent of the population across the five MML states on which the registry information is available. Therefore, the 1.3 percentage point increase in the probability of marijuana use we find among adults aged 21 or above is not likely to come exclusively from an increase in use among registered patients. Though we cannot test this directly, it suggests that there may also be a considerable spillover effect of MML implementation on recreational marijuana use or self-medication by the non-patient population.

Among adults aged 21 or above, we also find a 0.58 percent point or a 15 percent increase in the probability of almost daily/daily marijuana use (Panel B, Column 2, Row 1) attributable to MML implementation. Among adolescents and young adults aged 12-20, in contrast, no change in the probability or frequency of past-month marijuana use can be attributed to MML implementation (Panel A, Columns 1, 2 and 3).

With regard to marijuana use initiation during the preceding year, MML implementation leads to 0.32 percentage point or a 5 percent increase in the probability of first-time marijuana use among adolescents and young adults aged 12-20 (Panel A, Column 4, Row 1). Yet, the lack of a policy effect on the probability and frequency of past-month marijuana use among this age group suggests that many of these young people may be engaging in experimental use with relatively low health, behavioral, and social consequences. In other words, these findings are consistent with a scenario in which adolescents and young adults aged 12-20 who experiment with marijuana use in response to an MML are not transitioning to regular use, at least in the short term.

In contrast to the findings among adolescents and younger adults, we find no change in marijuana use initiation among those aged 21 or above (Panel B, Column 4) as a result of MML implementation, despite the aforementioned significant increases in any past-month marijuana use and almost daily/daily use (Panel B, Columns 1 and 2). These findings suggest that the adults who respond to an MML by increasing current and regular use come largely from those who first tried marijuana long before its medical use was permitted. After the introduction of an MML that helped reduce costs of marijuana use (i.e., market prices as well as non-market health, legal and social consequences), those with prior marijuana use experience would likely reinitiate or increase their marijuana use.

4.4.2 Estimated Effect of MML Implementation on Alcohol Use

To the extent that alcohol is a complement or substitute to marijuana, the effect of MML implementation on marijuana use may spread to alcohol use (Table 4.4). Our estimates indicate that, among adults aged 21 or above, MML implementation is not associated with the total number of drinks (Panel B, Column 1), but positively associated with the frequency of binge drinking. Our estimates indicate an effect size of 0.16 more binge drinking days or a relative increase of 10 percent (Panel B, Column 2, Row 1). The spillover increase in binge drinking implies a complementary relationship between marijuana use and high-dose alcohol consumption among adults aged 21 or above. Not only is this contemporaneous complementarity reflected in the independent measures of marijuana use and binge drinking, it is further confirmed by the measure of simultaneous use of the two substances. Among adults aged 21 or above, we find a 1.44 percentage point or a 22 percent increase in the probability of both marijuana use and binge drinking during the past month (Panel B, Column 3, Row 1) and a 0.82 percentage point or a 18 percent increase in the probability of marijuana use while drinking (i.e., in the same occasion) as a result of MML implementation (Panel B, Column 4, Row 1).

Among adolescents and young adults aged 12-20, we find no significant change in any measure of alcohol use (Panel A), which suggests that the increased marijuana use initiation we reported previously is unlikely to spread to underage drinking.

4.4.3 Immediate and Delayed Effect of MML Implementation on Other Downstream Outcomes

In addition to marijuana use and binge drinking, MML implementation may have a spillover effect on marijuana abuse/dependence, alcohol abuse/dependence, non-medical use of prescription pain medication, and the use of hard drugs such as heroin and cocaine. The progression from marijuana use and binge drinking to these downstream outcomes may be a gradual transition (Wagner and Anthony, 2002b). As such, we estimated not only the contemporary policy effect but also the one-year and two-year lagged policy effect (Table 4.5).

The effect arguably most salient to the public health implications of MMLs is the effect on marijuana abuse/dependence among adults aged 21 or above. We found a delayed policy effect on increasing the probability of marijuana abuse/dependence by a relative 10 percent (Panel B, Column 1, Rows 2 and 3). The increase in marijuana abuse/dependence of such magnitude is of concern. It suggests that those who used marijuana in response to MML implementation are at high risk of progressing to abuse/dependence.

For both age groups, we found neither an immediate nor a delayed effect of MML implementation on other downstream outcomes including alcohol abuse/dependence, non-medical use of prescription pain medication, heroin use and cocaine use.

4.4.4 Policy Heterogeneity between Key MML Provisions

Our main estimates, in essence, capture the average policy effect across all ten MMLs implemented between 2004 and 2012. However, the policy effect of each of these laws may not necessarily have the same magnitude or even the same direction. As noted by Pacula, et al. (2013), four key MML provisions, namely the ambiguity in “non-specific pain", the requirement for patient registry/renewal system, the allowance for retail dispensaries, and the permission for home cultivation, may have different implications for people's marijuana use behavior. Specifically, the "patient registry" provision may in effect reduce marijuana use in the general population. This protective effect of the "patient registry" provision, however, can be offset by the effect of "retail dispensary" provision which increases marijuana use significantly. In contrast to Pacula, et al. (2013), our study finds no consistent protective or offsetting effect in either provision (Tables 4.3 and 4.4, Panels A and B, Rows 2, 3, and 4). A plausible explanation is the discrepancy between the time when a "patient registry" provision or a "retail dispensary" provision was included a state's MML and the time when the state's registry/renewal system or its legal dispensaries actually began to operate (Andersen and Rees, 2014). Due to the controversy and complexity surrounding its implementation, the time lag between the effective date of a "retail dispensary" provision and the actual opening of the first medical marijuana store may be particularly long.[65] Although we find no consistent effect of "patient registry" or "retail dispensary", we observe a consistent and significant effect of the "non-specific pain" provision on increasing marijuana use, binge drinking and simultaneous use of marijuana and alcohol among adults aged 21 or above. The observed effect of "non-specific pain" provision suggests that including a generic term "chronic pain" in the eligible conditions for medical marijuana may extend the patient base to adults with less severe conditions or

[65]Andersen and Rees (2014) pointed out that, for instance, Colorado included a "retail dispensary" provision in its original MML effective in 2001, but medical marijuana dispensaries did not become commonplace until 2009. Moreover, Maine and Rhode Island added "retail dispensary" provisions to their MMLs in 2009, but the first legal dispensary in Maine did not open until 2011 and the first Rhode Island dispensary did not open until 2013.

possibly those who pretend to be pain patients. Nonetheless, considering the limited policy variations across the four MML provisions during our study period, the estimated individual effects of these provisions should be interpreted with caution.[66]

4.4.5 Policy Endogeneity of MML Adoption

There is a geographic concentration of MMLs: states that have adopted MMLs are all in the West and Northeast. This geographic similarity raises concern that there may be some past disturbances in marijuana use in these regions leading to their adoption of MMLs and not accounted for by the state fixed effects and the state-specific linear trends. In other words, MML adoption may be endogenous to marijuana use. To check for this potential policy endogeneity, specifications with a series of lagged and leading indicators for adopting an MML were estimated for the probability of past-month marijuana use (Table 4.6). We find that only the contemporary and 6-month lagged policy indicators had significant effects, and the indicators for approved but not implemented MMLs and the 12-month policy lag had moderate albeit imprecisely estimated effects. All the leads had small and statistically insignificant effects (Panel B, Column 2). These estimates suggest that it is in fact the policy shock from adopting an MML that drives the changes in marijuana use, rather than some past disturbances in marijuana use that drive the adoption of an MML.

[66]From a statistical standpoint, a substantial policy effect from one or two states could potentially account for the overall findings. We tested for the heterogeneous policy effect between states by replacing the single indicator for MML implementation with ten separate indicators for MML implementation in each of the MML states. We find, in most cases, across-the-board significant policy effects in the same direction, albeit with varied effect sizes (not shown). We cannot come to a conclusion, therefore, as to whether the heterogeneous policy effect comes from states' unique experiences with implementing the MMLs or their inclusion/exclusion of certain provisions.

4.4.6 State-Aggregate Effect of MML Implementation

To further check the robustness of our individual-level estimates with regard to serial correlation, we aggregated the data to the state level and estimated the effect of MML implementation on state-level prevalence rates of our main individual-level findings.[67] The previously highlighted policy effects on youth marijuana use initiation, as well as on adult past-month marijuana use, marijuana almost daily/daily use, marijuana abuse/dependence, past-month binge drinking, and simultaneous use of marijuana and alcohol remain significant with similar effect size in these state-level estimates (Table 4.7).

4.5 Discussion

Three main pieces of evidence from our study inform the policy discussions of MMLs. First, we find a significant effect of MML implementation on increasing marijuana use. Estimates suggest that the populations responsive to MMLs are adolescents and young adults aged 12-20 who experimented with marijuana for the first time and adults aged 21 or above who tried marijuana prior to the introduction of the law. This latter group also has an increased risk of progression to almost daily/daily marijuana use and marijuana

[67]In Column 1 and 3 of Table 4.7, we clustered the standard errors at the state level; while in Column 2 and 4, we removed the time-series information from the standard errors by averaging the pre-MML data and the post-MML data (Donald and Lang, 2007). We followed a two-step procedure described in Bertrand, Duflo, and Mullainathan (2001, pp. 267) to accommodate staggered adoption of the MMLs across states. As a result, the data were collapsed into pre- and post-MML two periods across 7 MML states. The standard errors were adjusted to take into account the smaller number of MML states (Donald and Lang, 2007).

abuse/dependence.[68] We caution that even if we assume the increases in any marijuana use and regular use come from those who use the drug for legitimate medical purposes, there may still be possibility that marijuana abuse/dependence would increase as a result of MML implementation. The effect of MML implementation on marijuana abuse/dependence constitutes a potential public health concern similar to that of prescription drug abuse epidemic in the U.S. (CDC, 2012).

Second, among those aged 21 or above, we find a spillover effect of MML implementation on the increasing frequency of binge drinking, possibly through increased use of the two substances simultaneously. The complementarity between marijuana use and binge drinking among adults of legal drinking age could magnify the expected harms of an MML. As Pacula and Sevigny (2014) commented, "even if consumption (of marijuana) were assumed to rise by 100 percent, the savings of liberalization policies would dwarf the known health costs associated with using marijuana. However, all potential savings … could be entirely erased, and tremendous losses incurred, if alcohol and marijuana turn out to be economic complements." The 10 percent increase in the frequency of binge drinking and the 18-22 percent increase in the probability of simultaneous marijuana and alcohol use[69] that we estimated may result in considerable

[68]A diagnosis of substance abuse/dependence, by definition, indicates that an individual is experiencing a cluster of psychological, physical, cognitive, and behavioral symptoms associated with substance use. The DSM-IV considers marijuana abuse and marijuana dependence to be valid psychiatric disorders, and marijuana abuse/dependence as experienced in clinical population and general population appears very similar to other substance abuse/dependence disorders (Budney, et al., 2007).

[69]The interaction between marijuana and alcohol may magnify the risks posed by the two substances individually (Liguori, Gatto, and Jarrett, 2002; Medina, et al., 2007).

economic and social costs from downstream health care expenditures and productivity loss (Naimi, et al., 2003).

It is worth noting that this implied complementarity between marijuana use induced by an MML and binge drinking does not necessarily contradict a conclusion made by Andersen, Hansen and Rees (2014) that the implementation of an MML results in reduced traffic fatalities, and that the reduction is more pronounced in those involving alcohol. A possible interpretation that may reconcile our findings with theirs is that MML implementation may lead to a shift of alcohol consumption from public places such as restaurants and bars to one's own home. Thus, we may see a reduction in the traffic fatalities, even if the implementation of an MML, in effect, increases binge drinking and simultaneous use of both alcohol and marijuana. The reduced traffic fatalities may result from the fact that those potential high-risk drivers are now more likely to stay at home and less likely to engage in driving.

Third, neither underage drinking among those aged 12-20 nor other substance use (i.e., non-medical use of prescription pain medication, heroin use and cocaine use) in both age groups is affected by MML implementation. In this regard, the often-voiced concerns about the potential gateway effect of marijuana is not supported by our findings. We caution that our study is not intended to refute the gateway hypothesis. Rather it suggests that the gateway effect is not likely to occur in the context of an MML: for those who respond to MML implementation and use marijuana, their marijuana use is not likely to act as a gateway to more dangerous substance use through the pharmacological properties of marijuana.[70] On the other hand, our findings do not lend support to an area of potential benefits of the law either, which is to benefit those who misuse opioid pain medication by helping them ease opiate withdrawal symptoms and achieve success in early recovery. However, NSDUH only includes questions about "non-medical use" of pain medication, so we cannot examine the effect of MML implementation on patients who use pain medication according to the prescription. The previously documented beneficial effect of an MML on reducing opioid overdose mortality may primarily come from this group of legitimate pain patients.[71] An MML may benefit these patients by allowing them to start with medical marijuana treatment in lieu of opioid pain medication or to switch partially or entirely from opioids to marijuana. Whether and to what extent the legitimate pain patients may benefit from MML implementation merit further investigation, but are beyond the scope of our study.

Taken together, our study findings provide evidence for a significant effect of MML implementation on increasing marijuana use, and a spillover effect among adults of legal drinking age from increased marijuana use to increased binge drinking. The findings do not, however, provide evidence to support other types of substance use spillovers such as underage drinking, pain medication misuse, and hard drug use.

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[70]Nonetheless marijuana may still be a gateway drug for other marijuana users through other pathways. For instance, those who use marijuana regardless of the laws or those who use marijuana in response to decriminalization may progress to hard drug use because marijuana introduces them to a shared market or subculture of hard drugs.

[71]More than 60 percent of the opioid pain medication users receive and take the drug according to the prescription (Bachhuber, et al., 2014).

TABLE 4.1 IMPLEMENTATION & KEY PROVISIONS OF STATE MEDICAL MARIJUANA LAWS

	APPROVED DATE	EFFECTIVE DATE	KEY STATUTORY PROVISIONS			
			Non-specific Pain	Patient Registry	Retail Dispensary+	Home Cultivation
2004-2012 (10 States)						
Vermont	2004/05	2004/07	2007/07	2004/07	n/a	2004/07
Montana	2004/11	2004/11	2004/11	n/a	n/a	2004/11
Rhode Island	2005/06	2006/01	2006/01	2006/01	2009/07	2006/01
New Mexico	2007/03	2007/07	n/a	2007/07	2007/07	2007/07
Michigan	2008/11	2008/12	2008/12	n/a	n/a	2008/12
New Jersey	2010/01	2010/10 †	2010/10	2010/10	2010/10	n/a
District of Columbia	2010/05	2010/07	n/a	2010/07	2010/07	n/a
Arizona	2010/11	2011/04	2011/04	2011/04	2011/04	2011/04
Delaware	2011/05	2011/07	2011/07	2011/07	2011/07	n/a
Connecticut	2012/05	2012/05 ‡	n/a	2012/05	n/a	n/a
1996-2003 (8 States)						
California	1996/11	1996/11	1996/11	n/a	1996/11	1996/11
Washington	1998/11	1998/11	1998/11	n/a	n/a	n/a
Oregon	1998/11	1998/12	1998/12	2007/01	n/a	1998/12
Alaska	1998/11	1999/03	1999/03	1999/03	n/a	1999/03
Maine	1999/11	1999/12	n/a	2009/12	2009/12	1999/12
Hawaii	2000/06	2000/12	2000/12	2000/12	n/a	2000/12
Colorado	2000/11	2001/06	2001/06	2001/06	2001/06	2001/06
Nevada	2000/11	2001/10	2001/10	2001/10	n/a	2001/10

Note:
Maryland passed two laws in 2003 and in 2011 favorable to medical marijuana, albeit not legalizing it;
+ Despite the allowance for retail medical marijuana dispensary under the laws, only four states actually opened their first dispensaries between 2004 and 2012, including Colorado (2005/07), New Mexico (2009/06), Maine (2011/04), and New Jersey (2012/12).
† The effective date of New Jersey MML is 2010/07 as specified in the statute, while the state governor Chris Christie delays its implementation;
‡ Most sections of Connecticut MML came into effect from its passage (2012/05), while a few sections on 2012/10.

TABLE 4.2 DESCRIPTIVE SUMMARY OF COVARIATES, SAMPLING-WEIGHT ADJUSTED

	AGE 12-20				AGE 21+			
	MML States		No & Always MML States		MML States		No & Always MML States	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
PANEL A: INDIVIDUAL-LEVEL COVARIATES								
# Age	16.0	(2.53)	16.0	(2.56)	48.0	(16.8)	47.5	(16.8)
% Male	51.4	(50.0)	51.2	(50.0)	48.1	(50.0)	48.0	(50.0)
Race/Ethnicity: Non-Hispanic White (ref.)								
% Hispanic/Latino	18.8	(39.1)	19.1	(39.3)	13.1	(33.8)	13.3	(33.9)
% Non-Hispanic African Black	12.8	(33.4)	15.0	(35.7)	10.0	(29.8)	11.5	(31.9)
% Non-Hispanic Asian	3.46	(18.3)	4.37	(20.5)	3.63	(18.7)	4.56	(20.8)
% Other Origins	4.15	(19.9)	2.71	(16.2)	2.43	(15.4)	1.87	(13.6)
Self-Reported Health: Excellent (ref.)								
% Very Good	42.6	(49.5)	41.5	(49.3)	36.5	(48.1)	35.9	(48.0)
% Good	21.0	(40.7)	21.4	(41.0)	27.1	(44.4)	27.7	(44.8)
% Fair/Poor	4.26	(20.2)	4.15	(19.9)	12.8	(33.5)	13.9	(34.6)
Cigarette Smoking: Non-Smoker (ref.)								
% Non-Daily Smoker	11.3	(31.7)	11.2	(31.5)	9.01	(28.6)	8.75	(28.3)
% Daily Smoker	6.75	(25.1)	6.36	(24.4)	15.8	(36.4)	16.1	(36.7)
Health Insurance: Uninsured (ref.)								
% Private Health Insurance	65.9	(47.4)	60.9	(48.8)	71.7	(45.0)	68.3	(46.5)
% Medicaid	22.9	(42.0)	24.5	(43.0)	8.59	(28.1)	8.14	(27.3)
% Other Health Insurance	3.15	(17.5)	4.02	(19.6)	7.82	(26.8)	8.84	(28.4)
Family Income: >200% FPL (ref.)								
% Living 100-200% FPL	19.8	(39.9)	22.9	(42.0)	17.0	(37.6)	19.3	(39.5)
% Living <100% FPL	19.4	(39.6)	22.1	(41.5)	10.3	(30.4)	12.0	(32.5)
Urbanicity: Non-CBSA (ref.)								
% Living in a Micropolitan	8.52	(27.9)	10.0	(30.0)	8.29	(27.6)	10.1	(30.0)
% Living in a Metropolitan	87.6	(33.0)	83.8	(36.8)	87.6	(33.0)	83.3	(37.3)
Marital Status: Married (ref.)								
% Never Married					22.5	(41.8)	21.3	(41.0)
% Separated/Divorces					6.91	(25.4)	6.42	(24.5)
% Widowed					13.7	(34.3)	14.4	(35.1)
Education Attainment: College Graduate (ref.)								
% Some College					24.9	(43.2)	25.5	(43.6)
% High School Graduate					29.3	(45.5)	29.9	(45.8)
% Less than High School					13.5	(34.2)	15.3	(36.0)
College Enrollment: Not Enrolled (ref.)								
% Part-Time Enrolled					3.81	(19.1)	3.31	(17.9)
% Full-Time Enrolled					3.86	(19.3)	4.33	(20.4)
Employment: Full-Time Employed (ref.)								
% Part-Time Employed					12.6	(33.2)	12.3	(32.8)
% Unemployed					4.49	(20.7)	4.15	(20.0)
% Not in Labor Force					29.0	(45.4)	29.2	(45.5)
PANEL B: STATE-LEVEL COVARIATES								
% Unemployment Rate	7.36	(2.60)	6.84	(2.36)	7.36	(2.60)	6.86	(2.36)
$ Average Personal Income (10K)	4.05	(0.90)	3.86	(0.54)	4.07	(0.90)	3.87	(0.54)
$ Median Household Income (10K)	5.64	(0.89)	5.25	(0.67)	5.65	(0.90)	5.24	(0.68)
Beer Tax Rates								
$ Specific Excise Tax (per gallon)	0.18	(0.07)	0.28	(0.25)	0.18	(0.07)	0.28	(0.25)
% Ad Valorem Tax (on-premises)	0.35	(1.84)	0.76	(3.05)	0.36	(1.88)	0.79	(3.10)
% Ad Valorem Tax (off-premises)	0.14	(1.06)	0.73	(2.97)	0.15	(1.15)	0.75	(3.01)
Number of Observations	≈ 46,700		≈ 222,800		≈ 56,400		≈ 267,500	

TABLE 4.3 ESTIMATED MARGINAL EFFECTS OF IMPLEMENTATION & PROVISIONS OF MMLS ON MARIJUANA USE

	(1)		(2)		(3)		(4)	
MARIJUANA USE OUTCOMES	% PAST-MONTH MARIJUANA USE		% MARIJUANA DAILY /ALMOST DAILY USE		COND. # MARIJUANA USE DAYS		% MARIJUANA USE INITIATION	
PANEL A: AGE 12-20								
MML Implementation	-0.43	(0.48)	-0.25	(0.17)	-0.28	(0.45)	**0.32****	(0.16)
MML Provisions:								
~ Non-Specific Pain	-0.05	(0.41)	-0.46	(0.28)	-0.74	(0.44)	0.43	(0.26)
~ Patient Registry	-0.74	(0.63)	-0.14	(0.27)	0.28	(0.36)	0.04	(0.23)
~ Retail Dispensary	**0.89****	(0.34)	-0.20	(0.36)	-0.46	(0.59)	0.45	(0.33)
~ Home Cultivation	0.12	(0.61)	0.43	(0.27)	0.93	(0.56)	0.18	(0.24)
Baseline Predicted Mean	[10.68]		[3.52]		[12.29]		[6.47]	
Number of Observations	≈ 269,500		≈ 269,500		≈ 28,600		≈ 213,900	
PANEL B: AGE 21+								
MML Implementation	**1.32****	(0.58)	**0.58****	(0.26)	0.17	(0.64)	0.15	(0.23)
MML Provisions:								
~ Non-Specific Pain	**1.56****	(0.73)	**0.86****	(0.42)	0.28	(0.88)	0.31	(0.78)
~ Patient Registry	-0.45	(0.73)	-0.35	(0.52)	0.55	(0.76)	-0.05	(0.44)
~ Retail Dispensary	-0.12	(0.79)	-0.09	(0.64)	-0.67	(0.85)	0.07	(0.53)
~ Home Cultivation	0.55	(0.76)	-0.10	(0.41)	-0.48	(0.76)	0.02	(0.77)
Baseline Predicted Mean	[9.33]		[3.78]		[14.15]		[0.92]	
Number of Observations	≈ 323,900		≈ 323,900		≈ 30,500		≈ 161,400	

Note:

Standard errors in parentheses are clustered at the state level;

Baseline mean is calculated as the average of predicted probabilities /counts when setting MML_{st} to 0 and leaving the other covariates as the observed values;

*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

TABLE 4.4 ESTIMATED MARGINAL EFFECT OF IMPLEMENTATION & PROVISIONS OF MMLS ON ALCOHOL USE

	(1)		(2)		(3)		(4)	
ALCOHOL USE OUTCOMES	# PAST-MONTH TOTAL ALCOHOL DRINKS		# BINGE DRINKING DAYS		% MARIJUANA USE & BINGE DRINKING		% MARIJUANA USE WHILE DRINKING	
PANEL A: AGE 12-20								
MML Implementation	-0.03	(1.74)	0.04	(0.18)	-0.63	(0.39)	-0.38	(0.49)
MML Provisions:								
~ Non-Specific Pain	-0.54	(2.86)	0.03	(0.03)	-0.59	(0.40)	0.07	(0.67)
~ Patient Registry	-0.53	(2.51)	-0.05	(0.04)	-0.39	(0.80)	-0.42	(0.63)
~ Retail Dispensary	0.65	(2.04)	0.06	(0.06)	0.54	(0.47)	0.87	(0.74)
~ Home Cultivation	0.52	(3.26)	-0.01	(0.04)	-0.03	(0.56)	-0.65	(0.64)
Baseline Predicted Mean	[7.76]		[0.66]		[6.41]		[4.10]	
Number of Observations	≈ 269,500		≈ 269,500		≈ 269,500		≈ 207,900	
PANEL B: AGE 21+								
MML Implementation	0.95	(1.18)	**0.16****	(0.08)	**1.44*****	(0.35)	**0.82***	(0.45)
MML Provisions:								
~ Non-Specific Pain	0.65	(1.56)	**0.19***	(0.10)	**1.03****	(0.49)	**1.23****	(0.59)
~ Patient Registry	0.27	(1.22)	-0.17	(0.11)	-0.10	(0.57)	-0.33	(0.55)
~ Retail Dispensary	0.47	(1.18)	0.07	(0.06)	0.21	(0.58)	-0.03	(0.66)
~ Home Cultivation	0.18	(1.52)	0.13	(0.09)	0.20	(0.62)	-0.57	(0.74)
Baseline Predicted Mean	[18.69]		[1.52]		[6.44]		[4.45]	
Number of Observations	≈ 323,900		≈ 323,900		≈ 323,900		≈ 250,500	

Note:
Standard errors in parentheses are clustered at the state level;
Baseline mean is calculated as the average of predicted probabilities /counts when setting MML_{st} to 0 and leaving the other covariates as the observed values;
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

TABLE 4.5 ESTIMATED IMMEDIATE & DELAYED MARGINAL EFFECT OF IMPLEMENTATION OF MMLS ON MARIJUANA ABUSE/DEPENDENCE, ALCOHOL ABUSE/DEPENDENCE, PRESCRIPTION PAIN MEDICATION MISUSE, COCAINE USE, & HEROIN USE

	(1)		(2)		(3)		(4)		(5)	
DOWNSTREAM OUTCOMES	% MARIJUANA ABUSE/DEPENDENCE		% ALCOHOL ABUSE/DEPENDENCE		% PRESCRIPTION PAINKILLER MISUSE		% COCAINE USE		% HEROIN USE	
PANEL A: AGE 12-20										
MML Contemporary	-0.07	(0.34)	-0.12	(0.52)	-0.05	(0.22)	0.03	(0.14)	0.008	(0.06)
MML Lags:										
~ 1-Year Lag	-0.10	(0.24)	-0.22	(0.54)	0.03	(0.35)	0.01	(0.23)	-0.01	(0.07)
~ 2-Year Lag	0.03	(0.27)	-0.28	(0.34)	-0.08	(0.42)	-0.01	(0.18)	-0.05	(0.11)
Baseline Predicted Mean	[4.59]		[7.77]		[8.26]		[2.41]		[0.26]	
Number of Observations	≈ 269,500		≈ 269,500		≈ 269,500		≈ 269,500		≈ 269,500	
PANEL B: AGE 21+										
MML Contemporary	0.19	(0.13)	0.65	(0.44)	-0.02	(0.39)	0.06	(0.18)	0.01	(0.11)
MML Lags:										
~ 1-Year Lag	**0.25****	(0.11)	0.37	(0.35)	-0.05	(0.21)	-0.11	(0.20)	0.007	(0.08)
~ 2-Year Lag	**0.23***	(0.12)	0.25	(0.55)	-0.09	(0.14)	-0.09	(0.21)	0.005	(0.09)
Baseline Predicted Mean	[2.30]		[10.87]		[6.65]		[3.28]		[0.32]	
Number of Observations	≈ 323,900		≈ 323,900		≈ 323,900		≈ 323,900		≈ 323,900	

Note:
Standard errors in parentheses are clustered at the state level;
Baseline mean is calculated as the average of predicted probabilities /counts when setting MML_{st} to 0 and leaving the other covariates as the observed values;
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

TABLE 4.6 ROBUSTNESS CHECK FOR POLICY ENDOGENEITY BY INCLUDING LEADS & LAGS

	(1)		(2)	
	% PAST-MONTH MARIJUANA USE		% PAST-MONTH MARIJUANA USE	
PANEL A: AGE 12-20				
MML Contemporary	-0.43	(0.48)	-0.81	(0.63)
MML Leads & Lags:				
~24-Month Lead (before approval)			0.27	(0.37)
~18-Month Lead			-0.25	(0.40)
~12-Month Lead			0.14	(0.93)
~ 6-Month Lead			0.57	(0.82)
~ Approved NOT Implemented			0.62	(0.69)
~ 6-Month Lag (after implementation)			-0.04	(0.34)
~12-Month Lag			-0.44	(0.68)
~18-Month Lag			-0.30	(0.64)
~24-Month Lag			0.47	(0.54)
Baseline Predicted Mean	[10.68]		[10.68]	
Number of Observations	≈ 269,500		≈ 269,500	
PANEL B: AGE 21+				
MML Contemporary	**1.32****	(0.58)	**1.02****	(0.46)
MML Leads & Lags:				
~24-Month Lead (before approval)			0.20	(0.71)
~18-Month Lead			-0.36	(0.64)
~12-Month Lead			0.18	(0.41)
~ 6-Month Lead			0.24	(0.55)
~ Approved NOT Implemented			0.52	(0.39)
~ 6-Month Lag (after implementation)			**0.73***	(0.38)
~12-Month Lag			0.41	(0.34)
~18-Month Lag			0.04	(0.47)
~24-Month Lag			0.11	(0.64)
Baseline Predicted Mean	[9.33]		[9.33]	
Number of Observations	≈ 323,900		≈ 323,900	

Note:
Standard errors in parentheses are clustered at the state level;
Baseline mean is calculated as the average of predicted probabilities /counts when setting MML_{st} to 0 and leaving the other covariates as the observed values;
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

TABLE 4.7 ROBUSTNESS CHECK FOR SERIAL CORRELATION BY STATE-LEVEL AGGREGATION

STATE-AGGREGATED RATES	AGE 12-20		AGE 21+	
	(1)	(2)	(3)	(4)
	State-Cluster	*2-Period Panels*†	*State-Cluster*	*2-Period Panels*†
MARIJUANA USE OUTCOMES				
% PAST-MONTH MARIJUANA USE	-0.63 (0.65)	-0.33 (0.50)	**1.34**** (0.52)	**1.17**** (0.56)
	[11.81]	[10.86]	[9.40]	[8.61]
% MARIJUANA ALMOST DAILY /DAILY USE	-0.22 (0.26)	-0.10 (0.24)	**0.56**** (0.22)	**0.51**** (0.29)
	[3.57]	[3.30]	[3.81]	[3.45]
% MARIJUANA USE INITIATION	**0.28*** (0.17)	**0.29**** (0.12)	0.14 (0.09)	0.11 (0.07)
	[6.85]	[6.28]	[0.94]	[0.86]
ALCOHOL USE OUTCOMES				
# PAST-MONTH DRINKS PER CAPITA	0.05 (0.79)	-0.06 (0.74)	0.69 (0.65)	0.72 (0.82)
	[8.28]	[7.62]	[19.02]	[18.38]
# BINGE DRINKING DAYS PER CAPITA	0.01 (0.03)	0.02 (0.05)	**0.18**** (0.08)	**0.12***** (0.04)
	[0.72]	[0.63]	[1.54]	[1.37]
% PAST-MONTH MARIJUANA USE & BINGE DRINKING	-0.54 (0.37)	**-0.65*** (0.39)	**1.22***** (0.38)	**1.29***** (0.45)
	[7.45]	[6.65]	[6.51]	[5.92]
% MARIJUANA USE WHILE DRINKING	-0.24 (0.43)	-0.15 (0.25)	**0.63**** (0.31)	**0.61*** (0.35)
	[4.65]	[4.12]	[4.45]	[3.52]
OTHER DOWNSTREAM OUTCOMES				
% MARIJUANA ABUSE/DEPENDENCE *(1-Year Lag)*	-0.26 (0.45)	-0.16 (0.39)	**0.35**** (0.18)	**0.41**** (0.20)
	[4.89]	[4.61]	[2.27]	[2.15]
% MARIJUANA ABUSE/DEPENDENCE *(2-Year Lag)*	-0.15 (0.44)	-0.02 (0.36)	**0.34*** (0.20)	0.26 (0.17)
	[4.89]	[4.60]	[2.29]	[2.16]
% ALCOHOL ABUSE/DEPENDENCE *(1-Year Lag)*	-0.10 (0.47)	-0.04 (0.44)	0.67 (0.51)	0.49 (0.41)
	[8.24]	[8.11]	[11.02]	[10.73]
% ALCOHOL ABUSE/DEPENDENCE *(2-Year Lag)*	-0.26 (0.46)	-0.28 (0.48)	0.21 (0.53)	0.28 (0.57)
	[8.22]	[8.10]	[11.03]	[10.74]
% PRESCRIPTION PAINKILLER MISUSE *(1-Year Lag)*	0.04 (0.50)	-0.04 (0.17)	-0.08 (0.36)	-0.10 (0.26)
	[8.75]	[8.51]	[6.76]	[6.47]
% CRACK/COCAINE USE *(1-Year Lag)*	-0.01 (0.20)	0.01 (0.15)	0.02 (0.16)	0.01 (0.21)
	[2.84]	[2.58]	[3.22]	[2.96]
% HEROIN USE *(1-Year Lag)*	-0.01 (0.09)	-0.02 (0.08)	-0.008 (0.11)	0.005 (0.10)
	[2.84]	[2.58]	[3.22]	[2.96]
Number of Observations	459	20	459	20

Note:

Standard errors in parentheses are clustered at the state level;

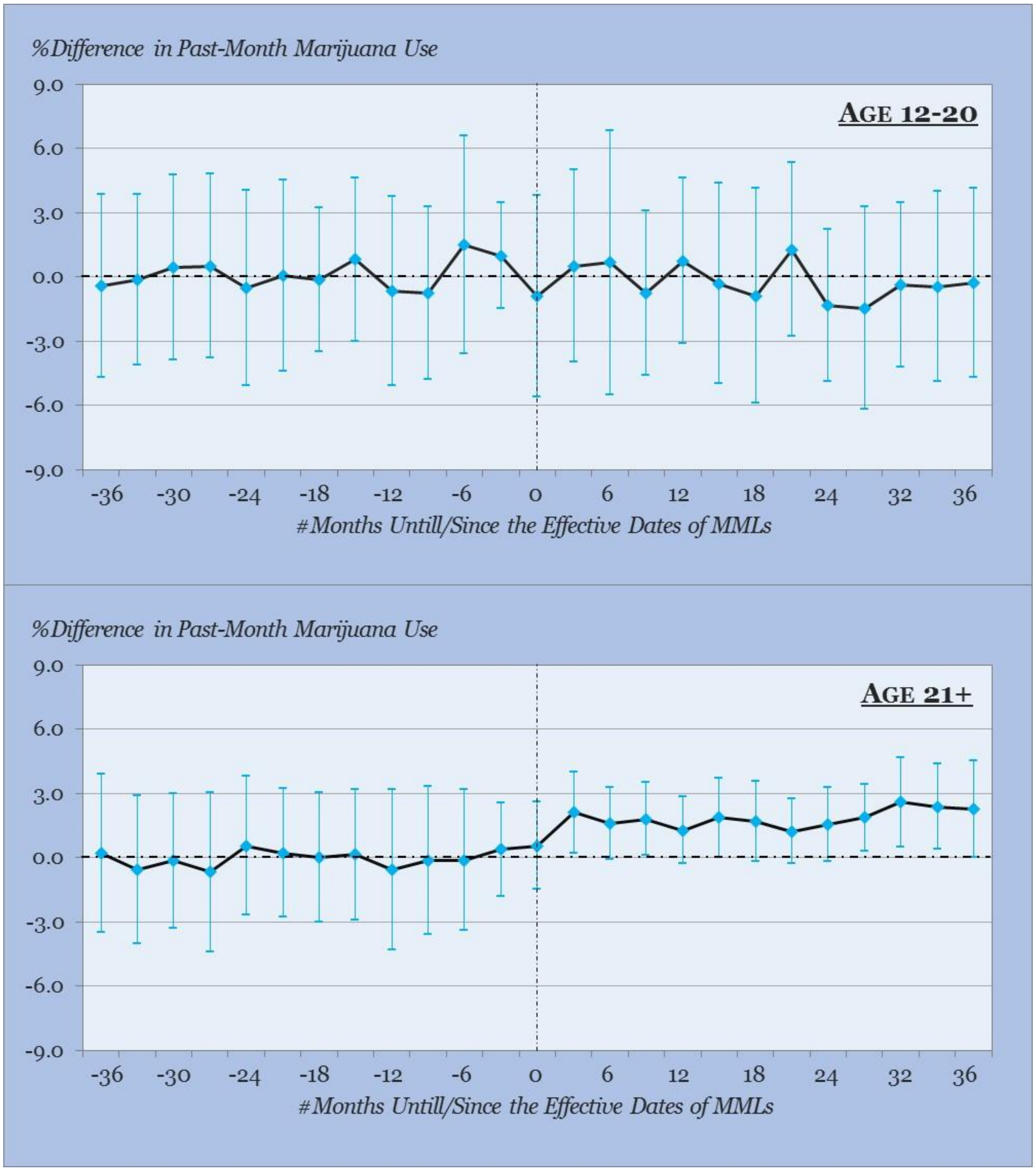
Baseline predicted mean in square brackets is calculated as the average of predicted probabilities /counts when setting MML_{st} to 0 and leaving the other covariates as the observed values;

† We average the pre-MML data and the post-MML data (Donald and Lang, 2007) following a two-step procedure described in Bertrand, Duflo, and Mullainathan (2001, pp. 267).
The second-step equation is estimated based on pre- and post-MML two-period panels of 10 "MML states". The standard errors are adjusted to take into account the small number of "MML states" (Donald and Lang, 2007);
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

TABLE 4.8 DSM-IV CRITERIA FOR SUBSTANCE ABUSE & SUBSTANCE DEPENDENCE

SUBSTANCE DEPENDENCE	SUBSTANCE ABUSE
A maladaptive pattern of substance use leading to clinically significant impairment or distress, as manifested by 3 or more of the following occurring at any time in the same 12-month period:	A maladaptive pattern of substance use leading to clinically significant impairment or distress, as manifested by 1 or more of the following occurring at any time in the same 12-month period:
1. Tolerance or markedly increased amounts of the substance to achieve intoxication or desired effect or markedly diminished effect with continued use of the same amount of substance; 2. Characteristic withdrawal symptoms or the use of certain substances to relieve or avoid withdrawal symptoms; 3. Use of a substance in larger amounts or over a longer period than was intended; 4. Persistent desire or unsuccessful efforts to cut down or control substance use; 5. Involvement in chronic behavior to obtain or use the substance, or recover from its effects; 6. Important social, occupational or recreational activities given up or reduced due to substance use; 7. Continued substance use despite knowledge of a persistent or recurrent physical or psychological problem that is likely to have been caused or exacerbated by the substance.	1. Recurrent substance use resulting in a failure to fulfill major role obligations at work, school, or home (e.g., repeated absences or poor work performance related to substance use; substance-related absences, suspensions, or expulsions from school; neglect of children or household); 2. Recurrent substance use in physically hazardous situations (e.g., driving an automobile or operating a machine when impaired by substance use); 3. Recurrent substance-related legal problems (e.g. arrests for obtaining or using the substance, substance-related disorderly conduct); 4. Continued substance use despite persistent or recurrent social and interpersonal problems caused or exacerbated by the substance (e.g., arguments with spouse about consequences of intoxication, physical fights).

FIGURE 4.1 TRENDS IN MARIJUANA USE RATES IN MEDICAL MARIJUANA LAW STATES RELATIVE TO THE CONTROL STATES



Note:
The differences in past-month marijuana use rate are equivalent to unadjusted difference-in-differences (DD) estimates that partial out the two-way fixed effects, but not adjust for individual- and state-level covariates or state-specific linear trends;
The time 0 is centered at the period when each medical marijuana law (MML) state started to implement its law, so the time 1 represents the first full month subsequent to the effective date of an MML;
We calculate the differences between each of the MML state and the control states during each month, then average them across all 10 MML states over a 3-month period (to smooth the fluctuations in monthly rate);
Whiskers indicate 95% confidence intervals.

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CHAPTER 5: Conclusion

"This Administration remains committed to a balanced public health and public safety approach to drug policy. This approach is based on science, not ideology."

~ President Barack Obama

Science demonstrates that substance use disorder (SUD) is a disease of the brain, a disease that can be prevented and treated, and from which individuals can recover. This revolutionary understanding of SUD during the past decade has propelled the nation to a rethink of its policy approach to substance control. Policymakers have called for evidence-based alternatives to the nation's substance control regime that has long been dominated by criminalization as the primary mechanism to deter substance use. This dissertation set out with the aim of providing rigorous evidence on the potential of health policy levers and financial incentives to encourage treatment seeking, discourage criminal involvement, and influence substance use behaviors.

5.1 Key Findings of Essay 1: State Parity Laws and Access to Treatment for Substance Use Disorder in the United States

The first essay provides evidence for the effect of the implementation and comprehensiveness of state SUD parity mandates on improving access to SUD treatment. The study first finds that implementation of SUD parity mandates in ten states between 2000 and 2008 leads to a significant improvement in SUD treatment use. State implementation of any SUD parity mandate increases the state-aggregate SUD treatment rate by a relative

9 percent ($p<0.01$). Furthermore, the increase in the SUD treatment rate is found to be more pronounced in states with more comprehensive parity mandates. The states with the most comprehensive SUD parity mandates see the largest increases in the SUD treatment rate (a 0.18 percent point or 13 percent increase, $p<0.05$).

5.2 Key Findings of Essay 2: The Effect of Substance Use Disorder Treatment Use on Crime

The second essay builds on the first and examines the potential spillovers of improved access to SUD treatment on reducing violent and property crimes. To address the potential endogeneity of the SUD treatment rate with respect to crime rates, the study exploits the exogenous variation in county-level SUD treatment rate induced by two state-level insurance policies, namely HIFA-waivers expansions and SUD parity mandates.

The findings first reveal a significant increase in county-level SUD treatment rate as a result of state implementation of HIFA-waiver expansions and SUD parity mandates. The implementation of HIFA-waiver expansions between 2001 and 2008 increases county-level SUD treatment rate by 20 percent ($p<0.001$). The implementation of SUD parity mandates increases the SUD treatment rate by 8 percent ($p<0.05$).

More importantly, the findings highlight that a 10 percent increase in county-level SUD treatment rate (i.e., equivalent to an increase by 1.28 per 1,000 residence) can reduce the robbery rate by 3 percent, reduce ($p<0.05$) the aggravated assault rate by 4 to 9 percent ($p<0.10$), and reduce the larceny theft rate by 2 to 3 percent ($p<0.05$). A back-of-the-envelope calculation shows that the benefit-cost ratio of SUD treatment with respect to crime reduction ranges from 1.6 to 3.0. Thus, in terms of cost-effectiveness, SUD treatment compares favorably with incarceration that has been shown to have a benefit-cost ratio centered around 1.5 and attributed to one third of the crime decline during the 1990s.

5.3 Key Findings of Essay 3: The Effect of Medical Marijuana Laws on Adolescent and Adult Use of Marijuana, Alcohol, and Other Substances

The third essay contributes to the literature by offering one of the first and most comprehensive estimates for the effect of state MML implementation on a variety of substance use outcomes in both adolescent and adult populations. Among adults aged 21 or above, the implementation of MMLs increases the probability of past-month marijuana use by 14 percent ($p<0.05$) and increases the probability of marijuana abuse/dependence by 18 percent ($p<0.01$). In addition to the effect on marijuana use, MML implementation also increases the frequency of past-month binge drinking among adults aged 21 or above by 10 percent ($p<0.05$) and increases their probability of marijuana use while drinking 10 percent ($p<0.10$).

Furthermore, the significant effects of MML implementation on adult marijuana use and excessive alcohol use are found to be concentrated in one key provision of the law, the inclusion of a generic "chronic pain" in the eligible conditions for medical marijuana without specifying diseases causing the pain. This "non-specific pain" provision may have unintended behavioral and public health implications by extending the patient base to adults with less severe conditions or possibly those who pretend to be pain patients.

The findings do not, however, lend support for other types of substance use spillovers (e.g., underage drinking, non-medical of prescription pain medication, and the use of hard drugs such as crack/cocaine and heroin) that can be attributed to state implementation of MMLs.

5.4 Main Conclusions

The three essays in my dissertation, collectively, take advantage of state policy experiments in insurance regulation, insurance expansion, and drug liberalization during the past decade, and offer new insights into the importance of health policies in the nation's substance control regime in terms of improving access to SUD treatment, and promoting public safety, and influencing substance use behaviors.

The first two essays provide evidence that, through improving coverage for SUD treatment, state HIFA-waiver expansions and SUD parity mandates can effectively improve access to SUD treatment. Improved access, in turn, can effectively and cost-effectively reduce substance use-related crimes.

When extrapolating the study findings to the potential impact of the ACA coupled with the MHPAEA, we may anticipate that the national health reform and federal parity legislation would further improve access to SUD treatment and reduce substance-related crimes beyond the estimated effects of previous state HIFA-waiver expansions and SUD parity mandates. As the ongoing implementation of the ACA is expected to dramatically reduce the number of uninsured Americans through the expansion of Medicaid programs and the creation of Health Insurance Marketplaces, a disproportionately large group of those with SUD would gain Medicaid or Marketplace coverage under the ACA (Garfield et al., 2011; Busch et al., 2014; Mark et al., 2015). Not only is SUD treatment recognized as an "Essential Health Benefit", it is also subject to the comprehensive SUD parity requirements under the federal parity act, the MHPAEA (Mechanic, 2012). The final rule on the MHPAEA extend the scope of parity requirements beyond quantitative restrictions to non-quantitative managed care mechanisms (e.g., medical necessity, prior authorization, and utilization review). Parity in non-quantitative areas can be critical for access to SUD treatment since these areas have not been addressed by previous state parity mandates but have featured heavily in the SUD treatment arrangements of today's public and private health plans (Barry and Huskamp, 2011; Busch, 2012).

A major area of uncertainty, however, lies in the capacity of behavioral health care system to meet the growing demand for SUD treatment. The SUD treatment system, in particular, has long been constrained by the inadequacy of the infrastructure, workforce shortages and low rate of reimbursement, and suffered rounds of major budget cuts in recent years. The system is likely to be stretched under full implementation of the ACA and the MHPAEA. There have been funding resources and innovative delivery models that can be leveraged to fill the capacity gap. For instance, the Obama Administration announced a 3-year (i.e., from 2014 to 2017) $100-million investment in community health centers and rural clinics to establish and extend SUD treatment services in these facilities. Moreover, the "Health Home" state plan option and the Prevention and Public Health Fund created under the ACA offer grant support to encourage the coordination and integration of SUD treatment and mainstream primary care. Capitalizing on those opportunities may help enhance the system capacity and translate the potential growth in demand for SUD treatment into tangible improvements in access and reductions in crimes.

The third essay provides comprehensive estimates for the effect of state MML implementation on a variety of substance use outcomes in both adolescent and adult populations. The study findings suggest that, in the context of MMLs, there may be a potential progression from marijuana use to abuse/dependence and a complementarity between marijuana use and excessive alcohol use among adults of legal drinking age. These findings add a caution that MMLs may have unintended consequences for a certain range of substance use behaviors that are interrelated and sensitive to policy changes. Nonetheless, neither underage drinking among those aged 12-20 nor other substance use (i.e., non-medical use of prescription pain medication, heroin use and cocaine use) in both age groups is affected by MML implementation.

For the states contemplating MMLs and other similar drug liberalization policies, the behavioral and public health implications found in my study may be brought to bear in comparing the costs and benefits likely to result from this type of legislation. Furthermore, states may wish to consider a proactive approach to mitigating the undesirable effects of marijuana liberalization. For instance, legislative provisions of MMLs could require the potency (i.e., THC content) of medical marijuana to be mandatorily disclosed and closely monitored in order to lower the risks of progression to marijuana abuse/dependence. In addition to market regulations, health education campaigns may also be put in place to inform individuals about the adverse effects of polydrug use, especially the simultaneous use of marijuana and alcohol.

In sum, the findings of this dissertation provide evidence that, through improving coverage for SUD treatment, insurance expansions and regulations can effectively improve access to SUD treatment. Improved access, in turn, can effectively and cost-effectively promote public safety by reducing substance use-related crimes. The findings also add caution that simply liberalizing drug laws and relaxing the criminalization regime may have unintended consequences for a certain range of substance use outcomes that are interrelated and sensitive to policy shocks. Thus, drug liberalization policies should be designed with public health concerns in mind and paired with additional public health strategies to mitigate an undesirable surge in substance use.

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