NBER WORKING PAPER SERIES

THE EFFECT OF SUBSTANCE USE DISORDER TREATMENT USE ON CRIME: EVIDENCE FROM PUBLIC INSURANCE EXPANSIONS AND HEALTH INSURANCE PARITY MANDATES

Hefei Wen
Jason M. Hockenberry
Janet R. Cummings

Working Paper 20537
http://www.nber.org/papers/w20537

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2014

We appreciate helpful comments on earlier drafts of this work from Chad Meyerhoefer, Sara Markowitz, Alison Cuellar, as well as participants at the 2014 ASHEcon Fifth Biennial Conference and the 2013 AcademyHealth's Annual Research Meeting, and seminar participants at Emory University. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Effect of Substance Use Disorder Treatment Use on Crime: Evidence from Public Insurance Expansions and Health Insurance Parity Mandates
Hefei Wen, Jason M. Hockenberry, and Janet R. Cummings
NBER Working Paper No. 20537
October 2014
JEL No. I11,I13,K14,K42

ABSTRACT

We examine the effect of increasing the substance use disorder (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. To address the potential endogeneity of the SUD treatment rate with respect to crime rate, we exploit the exogenous variation in the SUD treatment rate induced by two state-level policies, namely insurance expansions under the Health Insurance Flexibility and Accountability (HIFA) waivers and parity mandates for SUD treatment. Once we address the endogeneity issue, we are able to demonstrate an economically meaningful reduction in the rates of robbery, aggravated assault and larceny theft attributable to an increased SUD treatment rate. A back-of-the-envelope calculation shows that 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. Our findings suggest that expanding insurance coverage and benefits for SUD treatment is an effective policy lever to improve treatment use, and the improved SUD treatment use can effectively and cost-effectively promote public safety through crime reduction.

Hefei Wen
Emory University
Department of Health Management
and Policy
1518 Clifton Rd
Atlanta GA, 30322
hwen2@emory.edu

Jason M. Hockenberry
Department of Health Policy and Management
Rollins School of Public Health
Emory University
1518 Clifton Rd
Atlanta, GA 30322
and NBER
jason.hockenberry@emory.edu

Janet R. Cummings
Emory University
Department of Health Policy
and Management
1518 Clifton Rd
Atlanta GA, 30322
jrcummi@emory.edu

"Punishment is the last and the least effective instrument in the hands of the legislator for the prevention of crime."

~ John Ruskin (1819-1900)

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)[1].

[1] 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 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.

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 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[2]. 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 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)[3]. We show that previous policies

[2] 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).

[3] 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

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.

2. Background

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 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

demand for SUD treatment arising from the ACA expansions to be fully realized. However, this is outside the purview of this study.

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:

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

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 $Substance\ Use_{i',j,t}$, the law enforcement resources $Law\ Enforcement_{j,t}$, 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:

$$\boldsymbol{Substance\ Use_{i,j,t}} = f(\boldsymbol{SUD\ Treatment_{i,j,t}}, Law\ Enforcement_{j,t}, X_{3\ i,,j,t}, Z_{2\ j,t}) \quad (2)$$

$$\boldsymbol{Substance\ Use_{i',j,t}} = f(\boldsymbol{SUD\ Treatment_{i',j,t}}, Law\ Enforcement_{j,t}, X_{4\ i',,j,t}, Z_{2\ j,t}) \quad (3)$$

where substance use by the potential perpetrator $Substance\ Use_{i,j,t}$ and by the potential victim $Substance\ Use_{i',j,t}$ is a function of SUD treatment use $SUD\ Treatment_{j,t}$, the law enforcement resources $Law\ Enforcement_{j,t}$, 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:

$$\boldsymbol{Crime_{i,j,t}} = f(\boldsymbol{SUD\ Treatment_{i,j,t}}, \boldsymbol{SUD\ Treatment_{i',j,t}}, Law\ Enforcement_{j,t}, X_{1\ i,,j,t}, X_{2\ i',,j,t}, X_{3\ i,,j,t}, X_{4\ i',,j,t}, Z_{1\ j,t}, Z_{2\ j,t}) \quad (4)$$

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)[4]. 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)[5]. 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

[4] 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)

[5] 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.

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 productivity losses related to substance use (Donohue, Ewing and Peloquin 2001; Miron 1999)[6]. 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[7].

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 assistance, social skill development, mentoring and peer support, etc.),

[6] 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).

[7] 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).

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[8].

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 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).

2.2. Literature on SUD Treatment and Crime Reduction

[8] 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.

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. 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.

3.1 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*[9] ($Crime\ Rate_{c,s,t}$: number of crimes reported to all police agencies per 1,000 residents).

[9] 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)

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[10].

3.2 Primary Independent Variable: SUD treatment rate

The county-level SUD treatment rate was derived from facility-level information on annual SUD treatment counts in the N-SSATS 2000, 2002-2008[11]. N-SSATS covers all known specialty SUD treatment facilities[12] 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.

---

[10] 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).

[11] 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).

[12] 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.

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 Other Controls

County-level covariates include demographic characteristics, economic conditions, and law enforcement resources. Demographic characteristics including age distribution and racial/ethnic composition of the population were measured as the percentage of county residents who were (1) between the ages of 15 and 34[13], (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[14], and (8) unemployment rate[15]. 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[16]. We used both contemporaneous and one-

[13] 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).

[14] 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.

[15] 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.

[16] 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.

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[17] 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: (1) education, (2) police protection and correction, (3) hospital and health, and (4) 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: (5) state excise tax rates on beer[18], and (6) 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.

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:

---

[17] 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.

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

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

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 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 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[19] 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).

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[20] to accommodate the state-level instrumental variables we would introduce later to our analysis (see

[19] 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.

[20] 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.

Sections 5 and 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.

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.

5. HIFA-Waiver Expansions & SUD Parity Mandates: Instrumental Variables

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[21]. 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[22]may affect the SUD treatment rate and crime rates in the same direction[23]. 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 6 and 8 proceed with the statistical evidence on the strength and validity of the instruments.

5.2. Treatment Gap & Limited Insurance Coverage for SUD Treatment

[21] 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.

[22] 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."

[23] 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.

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[24] 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, 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).

---

[24] 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.

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.

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[25](Atherly, Coulam et al. 2012).

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

[25] 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.

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.

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[26] to provide benefits 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

[26] 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 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.

6. 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[27] (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[28] (i.e., Montana 2003-2008, Rhode Island 2003-2008, Maine 2004-2008, New Hampshire 2004-2008, Oregon 2007-2008, Wisconsin 2005-2008, and

[27] 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.

[28] "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).

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[29].

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:

$$\textbf{\textit{SUD Treatment Rate}}_{c,s,t} = \alpha_1 + \alpha_2\, \textbf{\textit{HIFA}}_{s,t} + \alpha_3\, X_{c,s,t} + \alpha_4\, X_{s,t} + \rho_c + \tau_t + \varepsilon_{c,s,t} \qquad (7)$$

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

Equation 6 estimates the effect of HIFA-waiver expansions alone on the SUD treatment rate, while Equation 7 estimates the effect of both instruments.[30] 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 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

[29] 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".

[30] 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.

to 8 percent increase. The F-statistics across all models exceed the critical values for Stock and Yogo (2002) weak instrument test[31].

7. Re-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 $\textit{SUD Treatment Rate}_{c,s,t}$ in Equation 8 with its predicted values derived from the respective first stage. The predicted values of $\textit{SUD Treatment Rate}_{c,s,t}$ capture the exogenous variation in the county-level treatment rate induced by the two state-level policies:

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

The top panel of Table 3 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

[31] 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.

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 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.

8. 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 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[32], while all the leads have insignificant effects with effect sizes close to zero[33]. 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.

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

[32] Table 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.

[33] 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.

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 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 5 top panel).

9. 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.[34]

On August 12, 2013, during a speech to the American Bar Association's House of Delegates in San Francisco, 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

[34] 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.

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)[35]. 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.

[35] 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 2.2.

TABLE 1. SUMMARY STATISTICS OF THE STUDY VARIABLES

Summary Statistics	County-Level *Mean (S.D.)*	CBSA-Level *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 2. ESTIMATED EFFECT OF SUD TREATMENT RATE ON COUNTY- & CBSA-LEVEL CRIME RATES: OLS RESULTS

OLS Estimates	**County-Level**		**CBSA-Level**	
	Unbalanced Panel (1)	Balanced Panel (2)	Unbalanced Panel (3)	Balanced Panel (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† (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† (0.001)**	**-0.002† (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. ESTIMATED EFFECT OF SUD TREATMENT RATE ON COUNTY- & CBSA-LEVEL 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**†	**-0.13***	**-0.24***	**-0.21***	-0.11	**-0.09**†	**-0.14***	**-0.12***
	(0.07)	**(0.07)**	**(0.11)**	**(0.10)**	(0.09)	**(0.05)**	**(0.05)**	**(0.04)**
Criminal Homicide	0.0002	0.001	0.0006	0.001	-0.002	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Forcible Rape	0.01	-0.01	-0.005	-0.02	0.01	0.006	**-0.02**†	-0.02
	(0.06)	(0.04)	(0.05)	(0.03)	(0.06)	(0.04)	**(0.01)**	(0.01)
Robbery	**-0.03**†	**-0.03***	**-0.04**†	**-0.03**†	**-0.03***	**-0.03***	**-0.02***	**-0.02***
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**
Aggravated Assault	**-0.12***	**-0.10**†	**-0.18***	**-0.16**†	**-0.08**†	-0.06	**-0.08***	**-0.07***
	(0.05)	**(0.05)**	**(0.09)**	**(0.09)**	**(0.05)**	(0.04)	**(0.04)**	**(0.04)**
Property Crime Rates	**-0.67***	**-0.72**†	**-0.67***	**-0.71**†	-0.52	**-0.58**†	-0.42	**-0.43**†
	(0.32)	**(0.41)**	**(0.31)**	**(0.42)**	(0.34)	**(0.35)**	(0.36)	**(0.26)**
Burglary	-0.05	-0.07	-0.05	-0.07	-0.03	-0.05	-0.01	-0.04
	(0.08)	(0.09)	(0.11)	(0.10)	(0.06)	(0.07)	(0.05)	(0.06)
Larceny Theft	**-0.50**†	**-0.55***	-0.52	**-0.54**†	**-0.43**†	**-0.46**†	-0.38	**-0.36**†
	(0.28)	**(0.30)**	(0.33)	**(0.34)**	**(0.26)**	**(0.27)**	(0.24)	**(0.22)**
Motor Vehicle Theft	-0.13	**-0.11**†	-0.10	-0.11	-0.06	-0.07	-0.02	-0.04
	(0.09)	**(0.06)**	(0.06)	(0.07)	(0.06)	(0.05)	(0.03)	(0.03)
Arson	0.001	-0.0004	0.004	-0.001	-0.004	-0.005	-0.0006	-0.002
	(0.005)	(0.01)	(0.003)	(0.01)	(0.005)	(0.006)	(0.002)	(0.004)
INSTRUMENTS: (Stage-I Dependent Variable: *SUD Treatment Rate per 1,000 residents*)								
HIFA (0/1)	**2.67*****	**2.60*****	**2.57*****	**2.50*****	**3.96****	**3.93****	**4.36****	**4.32****
	(0.41)	**(0.35)**	**(0.52)**	**(0.47)**	**(1.26)**	**(1.21)**	**(1.41)**	**(1.38)**
Parity (0/1)		**0.91***		**0.86***		**1.47***		**1.39***
		(0.42)		**(0.45)**		**(0.72)**		**(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 4. ESTIMATED EFFECT OF PAST & FUTURE POLICY CHANGES ON 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*****		**-0.11**†		**2.44*****		**-0.14****	
	(0.41)		**(0.08)**		**(0.52)**		**(0.05)**	
2-Year Before T_{HIFA}		-0.33		0.02		-0.32		0.02
		(0.72)		(0.02)		(0.72)		(0.02)
1-Year Before T_{HIFA}		-0.43		0.01		-0.43		0.02
		(0.67)		(0.02)		(0.67)		(0.02)
Year of T_{HIFA}		**2.05***		-0.07		**2.06***		-0.10
		(1.01)		(0.07)		**(0.98)**		(0.08)
1-Year After T_{HIFA}		**2.62*****		**-0.12**†		**2.64****		**-0.12***
		(0.52)		**(0.07)**		**(0.67)**		**(0.05)**
2-Year After T_{HIFA}		**1.59**†		**-0.08**†		1.06		**-0.07**†
		(0.95)		**(0.05)**		(0.86)		**(0.04)**
Parity (0/1)	**0.96***		-0.04		**0.87***		-0.03	
	(0.43)		(0.03)		**(0.44)**		(0.02)	
2-Year Before T_{Parity}		0.14		-0.008		0.14		-0.01
		(0.53)		(0.03)		(0.53)		(0.03)
1-Year Before T_{Parity}		-0.07		0.01		-0.07		0.01
		(0.43)		(0.07)		(0.43)		(0.07)
Year of T_{Parity}		**0.98***		-0.02		**0.98***		-0.01
		(0.48)		(0.02)		**(0.48)**		(0.01)
1-Year After T_{Parity}		0.55		**-0.02**†		0.55		**-0.02**†
		(0.34)		**(0.01)**		(0.34)		**(0.01)**
2-Year After T_{Parity}		0.56		-0.006		0.56		-0.007
		(0.35)		(0.004)		(0.35)		(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 5. ESTIMATED EFFECT OF SUD TREATMENT RATE ON CRIME RATES, ADDING STATE-SPECIFIC LINEAR TREND (robustness checks)

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): 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.

REFERENCES

Ainslie, George, and John Monterosso. 2003. "Hyperbolic discounting as a factor in addiction: A critical analysis" in Heather, Nick, and Rudy E. Vuchinich, eds. Choice, Behavioural Economics and Addiction: 35-61. Elsevier: Amsterdam, Netherlands.

Atherly, Adam, Bryan E. Dowd, Robert F. Coulam, and Gery Guy. 2012. "The effect of HIFA waiver expansions on uninsurance rates in adult populations." Health Services Research 47(3pt1), 939-962.

Banks, R. Richard. 2003. "Beyond profiling: Race, policing, and the drug war." Stanford Law Review, 56(3): 571-603.

Becker, Gary S., Kevin M. Murphy, and Michael Grossman. 2006. "The market for illegal goods: the case of drugs." Journal of Political Economy, 114(1): 38-60.

Belenko, Steven R., Nicholas Patapis, and Michael T. French. 2005. "The economic benefits of drug treatment: A critical review of the evidence for policy makers." Alcohol & Drug Problem Association of North America. Accessed 03/22/2013 from: http://www.fccmh.org/resources/docs/EconomicBenefits_of_Drug_Trx_02.05_.pdf

Bennett, Trevor, Katy Holloway, and David Farrington. 2008. "The statistical association between drug misuse and crime: a meta-analysis." Aggression and Violent Behavior, 13(2): 107-118.

Beronio, Kirsten, Sherry Glied, and Richard Frank. 2014 "How the Affordable Care Act and Mental Health Parity and Addiction Equity Act Greatly Expand Coverage of Behavioral Health Care." The Journal of Behavioral Health Services & Research, 2014 Issue: 1-19.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How much should we trust differences-in-differences estimates?." The Quarterly Journal of Economics, 119(1): 249-275.

Bishop, Tara F., Matthew J. Press, Salomeh Keyhani, and Harold Alan Pincus. 2014. "Acceptance of insurance by psychiatrists and the implications for access to mental health care." JAMA Psychiatry, 71(2): 176-181.

Bobo, Lawrence D., and Victor Thompson. 2006. "Unfair by design: The war on drugs, race, and the legitimacy of the criminal justice system." Social Research: An International Quarterly, 73(2): 445-472.

Brame, Robert, and Alex R. Piquero. 2003. "Selective attrition and the age-crime relationship." Journal of Quantitative Criminology, 19(2), 107-127.

Bureau of Labor Statistics (BLS). 2009. "National Compensation Survey: Health Plan Provisions in Private Industry in the United States, 2008." Washington, DC: U.S. Dept. of Labor Bureau of Labor Statistics (BLS). Accessed 03/22/2013 from: http://www.bls.gov/ncs/ebs/detailedprovisions/2008/ebbl0042.pdf

Chandler, Redonna K., Bennett W. Fletcher, and Nora D. Volkow. 2009. "Treating drug abuse and addiction in the criminal justice system: improving public health and safety." JAMA, 301(2): 183-190.

Caulkins, Jonathan, and Peter Reuter. 1998. "What price data tell us about drug markets." Journal of Drug Issues, 28: 593-612.

Centers for Medicare & Medicaid Services (CMS). 2001. "Health Insurance Flexibility and Accountability (HIFA) Demonstration Initiative." Baltimore, MD: U.S. Dept. of Health and Human Services (HHS) Centers for Medicare & Medicaid Services (CMS) Center for Medicaid and CHIP Services (CMCS); 2001. Accessed 03/22/2013 from: http://www.cms.hhs.gov/HIFA

Coughlin, Teresa A., Sharon K. Long, John A. Graves, and Alshadye Yemane. 2006. "An early look at ten state HIFA Medicaid waivers." Health Affairs, 25(3), w204-w216.

Cuellar, Alison E., and Jehanzeb Cheema. 2012. "As roughly 700,000 prisoners are released annually, about half will gain health coverage and care under federal laws." Health Affairs 31(5): 931-938.

Cummings, Janet R., Hefei Wen, Michelle Ko, and Benjamin G. Druss. 2014. "Race/ethnicity and geographic access to Medicaid substance use disorder treatment facilities in the United States." JAMA Psychiatry, 71(2): 190-196.

Dackis, Charles, and Charles O'Brien. 2005. "Neurobiology of addiction: treatment and public policy ramifications." Nature: Neuroscience, 8(11): 1431-1436.

Dave, Dhaval, and Swati Mukerjee. 2011. "Mental health parity legislation, cost-sharing and substance-abuse treatment admissions." Health Economics, 20(2): 161-183.

Donald, Stephen G., and Kevin Lang. 2007. "Inference with difference-in-differences and other panel data." The Review of Economics and Statistics, 89(2): 221-233.

Donohue III, John J., Benjamin Ewing, and David Pelopquin. 2011. "Rethinking America's illegal drug policy." National Bureau of Economic Research (NBER) Working Paper No. w16776.

Everitt, Barry J., and Trevor W. Robbins. 2005. "Neural systems of reinforcement for drug addiction: from actions to habits to compulsion." Nature: Neuroscience, 8(11): 1481-1489.

Fellner, Jamie. 2009. "Race, drugs, and law enforcement in the United States." Stanford Law & Policy Review, 20: 257-292.

French, Michael T., and Ioana Popovici. 2011. "That instrument is lousy! In search of agreement when using instrumental variables estimation in substance use research." Health Economics, 20(2): 127-146.

Gerstein, Dean R., and Lawrence S. Lewin. 1990. "Treating drug problems." New England Journal of Medicine, 323(12): 844-848.

Goldstein, Paul J. 2003. "The drugs/violence nexus." Crime, 4: 96.

Gove, Walter R., Michael Hughes, and Michael Geerken. 1985. "Are uniform crime reports a valid indicator of the index crimes? An affirmative answer with minor qualifications." Criminology, 23(3): 451-502.

Kaiser Family Foundation (KFF). 2013. "Medicaid: A Primer: Key Information on the Nation's Health Coverage Program for Low-Income People." Menlo Park, CA: The Henry J. Kaiser Family Foundation (KFF) The Kaiser Commission on Medicaid and the Uninsured; 2013. Accessed 03/22/2013 from: http://kaiserfamilyfoundation.files.wordpress.com/2010/06/7334-05.pdf

Kalivas, Peter W., and Nora D. Volkow. 2005. "The neural basis of addiction: a pathology of motivation and choice." American Journal of Psychiatry, 162(8): 1403-1413.

Katz, Lawrence, Steven D. Levitt, and Ellen Shustorovich. 2003. "Prison conditions, capital punishment, and deterrence." American Law and Economics Review, 5(2): 318-343.

Kuziemko, Ilyana, and Steven D. Levitt. 2004. "An empirical analysis of imprisoning drug offenders." Journal of Public Economics, 88(9): 2043-2066.

Leshner, Alan I. 1999. "Science-based views of drug addiction and its treatment." JAMA, 282(14): 1314-1316.

Levitt, Steven D. 1996. "The effect of prison population size on crime rates: evidence from prison overcrowding litigation." The Quarterly Journal of Economics, 111(2): 319-351.

Levitt, Steven D. 1997. "Using electoral cycles in police hiring to estimate the effect of police on crime." American Economic Review, 87(3): 270-290.

Levitt, Steven D. 2004. "Understanding why crime fell in the 1990s: four factors that explain the decline and six that do not." The Journal of Economic Perspectives, 18(1): 163-190.

Lynch, James P., and John P. Jarvis. 2008. "Missing data and imputation in the uniform crime reports and the effects on national estimates." Journal of Contemporary Criminal Justice, 24(1): 69-85.

Mark, Tami L., Katharine R. Levit, Rosanna M. Coffey, David R. McKusick, Henrick J. Harwood, Edward C. King, Ellen Bouchery, James S. Genuardi, Rita Vandivort-Warren, Jeffrey A. Buck, Katheryn Ryan. 2007. "National Expenditures for Mental Health Services and Substance Abuse Treatment, 1993-2003." Rockville, MD: U.S. Dept. of Health and Human Services (HHS) Substance Abuse and Mental Health Services Administration (SAMHSA) Center for Mental Health Services (CMHS); 2007. Accessed 03/22/2013 from http://store.samhsa.gov/shin/content//SMA07-4227/SMA07-4227.pdf

Markowitz, Sara. 2005. "Alcohol, drugs and violent crime." International Review of Law and Economics, 25(1): 20-44.

McCollister, Kathryn E., Michael T. French, and Hai Fang. 2010. "The cost of crime to society: new crime-specific estimates for policy and program evaluation." Drug and Alcohol Dependence, 108(1): 98-109.

McLellan, A. Thomas, David C. Lewis, Charles P. O'Brien, and Herbert D. Kleber. 2000. "Drug dependence, a chronic medical illness." JAMA, 284(13): 1689-1695.

McLellan, A. Thomas, George E. Woody, David Metzger, James McKay, Jack Durell, Arthur I. Alterman, and Charles P. O'Brien. 1996. "Evaluating the effectiveness of addiction treatments: reasonable expectations, appropriate comparisons." The Milbank Quarterly, 74(1): 51-85.

Mechanic, David. 2014. "More people than ever before are receiving behavioral health care in the United States, but gaps and challenges remain." Health Affairs, 33(8): 1416-1424.

Miller, Ted R., David T. Levy, Mark A. Cohen, and Kenya L. C. Cox. 2006. "Costs of alcohol and drug-involved crime." Prevention Science, 7(4): 333-342.

Miron, Jeffrey A. 1999. "Violence and the US prohibitions of drugs and alcohol." American Law and Economics Review, 1(1): 78-114.

Model, Karyn E. 1993. "The effect of marijuana decriminalization on hospital emergency room drug episodes: 1975–1978." Journal of the American Statistical Association, 88(423): 737-747.

Morrissey, Joseph, Gary Cuddeback, Alison E. Cuellar, and Henry Steadman. 2007. "The role of Medicaid enrollment and outpatient service use in jail recidivism among persons with severe mental illness." Psychiatric Services, 58(6): 794-801.

O'Donoghue, Ted, and Matthew Rabin. 1999. "Doing it now or later." American Economic Review, 89(1): 103-124.

Office of National Drug Control Policy (ONDCP). 2012. "Arrestee Drug Abuse Monitoring Program II 2010 Annual Report." Washington, DC: Office of National Drug Control Policy, Execrutive Office of the President; 2012. Accessed 03/22/2013 from: http://www.whitehouse.gov/sites/default/files/ondcp/policy-and-research/adam2010.pdf

Prendergast, Michael L., Deborah Podus, Eunice Chang, and Darren Urada. 2002. "The effectiveness of drug abuse treatment: a meta-analysis of comparison group studies." Drug and Alcohol Dependence, 67(1): 53-72.

Rajkumar, Andrew S., and Michael T. French. 1997. "Drug abuse, crime costs, and the economic benefits of treatment." Journal of Quantitative Criminology, 13(3): 291-323.

Shea, John. 1997. "Instrument relevance in multivariate linear models: a simple measure." Review of Economics and Statistics, 79(2): 348-352.

Sommers, Benjamin D., Katherine Baicker, and Arnold M. Epstein. 2012. "Mortality and access to care among adults after state Medicaid expansions." New England Journal of Medicine, 367(11): 1025-1034.

Substance Abuse and Mental Health Services Administration (SAMHSA). 2011. "Results from the 2010 National Survey on Drug Use and Health: Summary of National Findings." Rockville, MD: U.S. Dept. of Health and Human Services (HHS) Substance Abuse and Mental Health Services Administration (SAMHSA) Center for Behavioral Health Statistics and Quality (CBHSQ); 2011. Accessed 03/22/2013 from: http://www.samhsa.gov/data/NSDUH/2k10ResultsRev/NSDUHresultsRev2010.htm

Substance Abuse and Mental Health Services Administration (SAMHSA). 2006. "State Mandates for Treatment for Mental Illness and Substance Use Disorders." Rockville, MD: U.S. Dept. of Health and Human Services (HHS) Substance Abuse and Mental Health Services Administration (SAMHSA) Center for Mental Health Services (CMHS); 2006. Accessed 03/22/2013 from: http://store.samhsa.gov/shin/content/SMA07-4228/SMA07-4228-A.pdf

Stock, James H., and Motohiro Yogo. 2002. "Testing for weak instruments in linear IV regression." National Bureau of Economic Research (NBER) Working Paper No. w284.

Taxman, Faye S., Craig E. Henderson, and Steven Belenko. 2009. "Organizational context, systems change, and adopting treatment delivery systems in the criminal justice system." Drug and Alcohol Dependence, 103: S1-S6.

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.

Wu, Li-Tzy, Anthony C. Kouzis, and William E. Schlenger. 2003. "Substance use, dependence, and service utilization among the US uninsured nonelderly population." American Journal of Public Health, 93(12), 2079.