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MENTAL HEALTH PARITY LEGISLATION, COST-SHARING AND SUBSTANCE ABUSE TREATMENT ADMISSIONS

Dhaval M. Dave
Swati Mukerjee

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ABSTRACT

Treatment is highly cost-effective in reducing an individual's substance abuse (SA) and associated harms. However, data from Treatment Episodes (TEDS) indicate that per capita treatment admissions have remained flat (1992-2003) despite an increase in heavy drug use. Only 16 percent of individuals with clinical SA disorders receive any treatment, and almost half point to accessibility and cost constraints as barriers to care. This study investigates the impact of state mental health parity legislation on treatment admission flows. Fixed effects specifications indicate that mandating comprehensive parity for mental health and SA disorders raises the probability that a treatment admission is privately insured, lowering costs for the individual. While there is some crowd-out of charity care for private insurance, mandates reduce the uninsured probability by a net 1.4-2.4 percentage points (5% relative to the sample mean). States which mandate comprehensive parity also see an increase in total treatment admissions, relative to states which do not support parity. Thus, increasing cost-sharing and reducing financial barriers for the at-risk population may aid in their obtaining adequate SA treatment. However, the effect sizes are muted due to supply/capacity constraints, suggesting that demand-focused interventions need to be complemented with policies that support treatment facilities and providers.

Dhaval M. Dave
Bentley University
Department of Economics
175 Forest Street, AAC 195
Waltham, MA 02452-4705
and NBER
ddave@bentley.edu

Swati Mukerjee
Bentley University
175 Forest Street, AAC 183
Waltham, MA 02452
smukerjee@bentley.edu

I. Introduction

The U.S. market for illicit drugs is valued upwards of $60 billion annually, with over 70 percent of the expenditures attributed to cocaine and heroin (Office of National Drug Control Policy, 2001). The resulting societal costs that such drug consumption imposes in the form of crime, health care costs, and productivity losses, are estimated at $181 billion for 2002 (ONDCP, 2004). Despite the more than $35 to $40 billion a year that is being spent as part of a steadily increasing federal drug control budget, the prevalence of substance abuse remains high with 20 million individuals reporting current (past month) use of illicit drugs and 7 million afflicted with substance dependence or abuse disorders (2006 National Survey of Drug Use and Health).

Besides primary prevention, the effective reduction of drug use and related harms entails lowering intake among current, particularly hardcore, users since the consumption of drugs in the U.S. is far from uniform. The distribution is highly skewed with the highest tail of heavy users accounting for as much as 90 percent of total cocaine and heroin consumption (Dave, 2006, 2008). That drug abuse treatment can successfully reduce an individual's drug use and associated harms including adverse health effects, crime, HIV infection, and unemployment, relative to no treatment is shown in an extensive body of literature.[1] For instance, in a large sample of opiate-dependent individuals in Philadelphia, 21 percent of treated individuals tested positive for HIV after seven years versus 51 percent in a matched no-treatment group (McLellan et al., 2000). Furthermore, cost-benefit studies have consistently shown that treatment imparts positive economic returns with benefits far exceeding costs.[2] Rajkumar and French (1997) conclude, for instance, that conservative benefits of avoided criminal activity and intangible victimization costs alone outweigh even the most expensive residential treatment programs. According to California's Drug and Alcohol Treatment Assessment, a dollar invested in substance abuse treatment yields a return of seven

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[1] See Reuter and Pollack (2006), Stewart et al. (2002), Institute of Medicine (2000), McLellan et al. (2000) and Metzger (1998).

[2] See Cartwright (1998, 2000) for a good discussion of the methodological issues, the modeling of costs and benefits for drug abuse treatment, and a review of the cost-benefit literature.

dollars from reduced health care costs, crime, lost-productivity, and other prevented adverse consequences (Delaney et al., 2000).

Studies also show that drug abuse treatment may be cost-effective relative to other alternatives. The cost of treatment (about $12,500 for residential treatment and $3,100 for outpatient treatment per person-year) is significantly less than the cost of incarceration (about $40,000 per person-year) (Schneider Institute of Health Policy, 2001). Saffer et al. (2001) examine state-level expenditures on criminal justice and public health programs. They calculate cost savings of 30 percent in using treatment to deter an additional individual from consuming drugs compared with using enforcement and the criminal justice system.[3] Rydell et al. (1996) show that controlling demand by treating heavy substance users is more cost-effective than controlling supply through source country control, interdiction, or domestic enforcement.

In spite of this apparent consensus on the cost-effectiveness of drug abuse treatment, there has been a gradual reallocation of federal funding towards supply reduction activities and away from demand reduction (Figure 1). For instance, the share of the federal drug control budget devoted towards law enforcement, interdiction, and border control has steadily risen from 47 to 64 percent from 1995 through 2007, whereas the share of treatment (including direct funding for treatment programs and treatment research) has declined from 35 to 22 percent. Prevention activities declined in share from 18 to 14 percent.[4]

Concurrent with these trends, substance abuse (SA) treatment admissions have failed to keep up with recent increases in substance abuse. While data from general population surveys showed a declining trend in the prevalence of illicit drugs in the 1990s, more recent years have indicated an uptake. For instance, past month prevalence in the National Surveys on Drug Use and Health (NSDUH) increased

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[3] Cost-effectiveness studies comparing drug abuse treatment with other alternatives should be interpreted with caution, however, since the various approaches are not necessarily alternatives or mutually exclusive. Treatment and criminal justice may reinforce each other. For instance, enforcement activities affect treatment decisions and referrals into treatment sometimes originate in the criminal justice system through drug courts or alternative sentencing.

[4] There is a break in the data series in 2001, due to a restructuring of how the federal drug control budget is reported. However, this does not affect broad comparisons of the relative shares.

from 6.3 percent in 1999 to 8.2 percent in 2006. Such data, however, paint an incomplete picture since self-reported national surveys fail to capture sub-populations like the homeless or arrestees, who may behave very differently from the population-at-large. These surveys are therefore not reflective of hardcore users, who impose the heaviest costs on society and are the target of much illegal drug policy.[5] More objective indicators of heavy drug consumption show a rising trend. For instance, drug-related hospital emergency department (ED) episodes increased from 145 (per 100,000 people) in 1978 to 261 in 2002.[6] There were a total of 19,698 deaths from drug-induced causes in 2000, an increase of 108 percent over ten years. Between 1992 and 2002, the overall costs of drug abuse increased by 68 percent (ONDCP, 2004). Figures 2 and 3 document the trends for population-adjusted (ages 15+) drug-related hospital emergency department (ED) visits and SA treatment admissions from 1992 till 2003. Total drug-related ED visits increased by over 35 percent over this period, in contrast to a relatively flat trend in treatment admissions. While ED visits specifically related to cocaine and heroin use have increased by about 53 percent over this period, treatment admissions related to these substances have increased by less than six percent, with more recent years suggesting a downward trend. During the mid-1990s, treatment admissions were falling even as indicators of hardcore drug use were rising.

While treatment is cost-beneficial for society, it represents a significant cost barrier for drug users. Of the over seven million individuals with clinical substance abuse disorders (2006 National Survey of Drug Use and Health), only 16 percent received treatment at some point in the past year, implying that almost six million went untreated. Fifty percent of individuals who require treatment but do not obtain it, point to cost constraints or lack of coverage as an impediment to receiving care. Thus, an individual's

[5] For instance, heroin use is virtually non-existent in the National Surveys of Drug Use and Health (NSDUH). Less than 0.1 percent of the sample reported current heroin use in 2005.
[6] Part of this growth in drug-related hospital ED visits may be due to an increase in the purity of illicit substances. The steady trend in drug-related ED visits however does not perfectly mimic the trends in drug purity. For instance, the average purity of powder cocaine reached a high in the early to mid-1980s, declined somewhat in the early 1990s, remained stable for the rest of the decade, and has recently shown signs of rising again. Heroin purity increased dramatically from the early 1980s until about 1993, and has remained relative stable since. In contrast, cocaine and heroin-related ED visits have mostly exhibited a steady upward trend over the past 25 years. Some of the increase in ED admissions may also be driven by inexperienced drug users, though generally all age groups share in the rising trend in drug-related ED visits.

decision to seek substance abuse treatment also depends on ability to pay, which is affected by access to insurance that covers treatment for mental illness and substance disorders, and subsequent cost-sharing.

The prevalence of substance use is almost twice as high among individuals with mental illnesses. Given the high comorbidity between SA disorders and other mental illnesses (Saffer and Dave, 2005), effectively treating addiction requires full access to treatment services. While the pathology between mental disorders and substance use is complex, at least part of the correlation represents a causal link from mental disorders to substance use that is consistent with a self-medication hypothesis (Saffer and Dave, 2005). Thus, treating mental illnesses may also have the external benefit of reduction in substance use (and vice versa).

Public and private insurers have not covered treatment for SA disorders or mental illnesses on the same terms as other physical illnesses. Though 61 percent of individuals with a SA disorder report having private health insurance, 20 percent of insured individuals report lack of affordability or coverage as reasons for not obtaining treatment. The Mental Health Parity Act (MHPA) of 1996, which took effect on January 1, 1998, aimed at addressing this coverage disparity. It mandated that large employers (with more than 50 employees) offering group health insurance must offer coverage for mental illness equal to the lifetime and annual caps set for physical illnesses. However, the 1996 federal law did not fully address unequal coverage since insurers may still charge higher co-payments and deductibles and set lower treatment limits for mental illnesses. In addition, the federal law did not apply to substance abuse disorders and chemical dependency, and exemptions were available if the employer expected insurance costs to increase by more than one percent. More importantly, the law only applied to policies that offered mental health benefits in the first place - it did not require plans to offer mental health coverage if they do not already do so. Amendments to the 1996 MHPA were recently signed into law as part of the Emergency Economic Stabilization Act of 2008 and will take effect on January 1, 2010 for most group health plans. Parity is extended to all terms of the health plan including deductibles, copayments, coinsurance and out-of-pocket expenses, provided that the plan already offers mental health or substance use disorder benefits. However, the amendments still do not require a group health plan to provide mental health or substance use disorder coverage if it does not already do so.[7]

To rectify the loopholes in the 1996 MHPA, several states have passed legislation that mandates comprehensive parity beyond the federal law, requiring insurers to provide the same level of benefits for mental illness or substance abuse as for other physical disorders and diseases and to do so at similar terms. Currently, six states have laws mandating full parity for mental and physical health, and 18 states plus D.C. mandate some type of treatment parity for SA disorders. Thus, 32 states do not offer any type of parity for SA treatment. We will exploit these state-level differences in the laws and their timing of enactment to analyze the impact of such mandates on flows into SA treatment admissions. By improving access to treatment and reducing out-of-pocket costs, such mandates may have a positive impact on the decision to seek treatment, though the effect may depend on whether the laws effectively expand access for individuals in need and facilitate significant cost-sharing. The results from this analysis will be informative in assessing how the amendments to the MHPA may potentially affect substance abuse treatment admissions once they take effect in 2010. There is also room for further policy interventions if the state mandates are found to be effective, since the MHPA amendments do not mandate that plans offer mental health coverage, only that the coverage is on equal terms if it is already offered.

As a secondary aim, this study also examines the link between illicit drug prices and substance abuse treatment admissions. Much of current drug control policy in the United States focuses on supply-reduction programs aimed at stopping the flow of drugs and apprehending and punishing drug offenders. Such enforcement, by increasing the cost of supplying drugs to the U.S. market, is thought to act as a non-monetary tax and raise the transaction price of drugs (Reuter and Kleiman, 1986). Higher drug prices reduce drug use, and may motivate individuals to seek SA treatment, which in turn is likely to result in

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[7] In a 1995 survey of 171 large employers, virtually all plans covered some basic mental health and substance abuse services (though outpatient services were generally restricted by a maximum dollar amount per year). However, with respect to more intensive treatment (non-hospital residential care, methadone maintenance), only between 18 % to 36 % of plans offered any type of coverage for such services (Buck and Umland, 1997). Since the survey oversampled the largest of employers (almost half had 5,000 or more employees while nationally just a tenth of a percent of employers are this large), the results are not representative.

greater sustained abstinence or reduction in drug use, relative to short-term consumption responses to higher prices sans treatment. Since manipulating prices is one instrument of control that the public sector can exercise on the market for addictive unhealthy substances, empirical estimates of the relation between price variations and treatment flows would be relevant to informing public policy. Examining the relation between illicit drug prices and treatment also presupposes that spending on enforcement and treatment are not necessarily separate -- there may be synergies between the two as policies impacting drug prices may also affect treatment. The empirical link between drug prices and treatment admissions can also indirectly inform on the overall drug price-participation elasticity.

With low prevalence of substance abuse treatment and reporting biases, population and household surveys do not provide adequate sample sizes to facilitate rigorous analyses of state or locality-specific policy factors. This study employs administrative data on almost 19 million treatment admissions spanning 1992 through 2003, derived from the Treatment Episode Data Set (TEDS), matched with state and metro-area drug price measures and insurance parity legislation. Fixed-effects specifications are estimated to account for statistical endogeneity and control for unmeasured factors that may be correlated with policies and treatment admissions.

The remainder of the study proceeds as follows. Section 2 reviews some of the relevant literature. Section 3 describes the data and compares some socio-demographic trends in drug use and treatment admissions. Section 4 outlines the analytical models that guide the empirical specifications. Section 5 presents results from the multivariate models, while the concluding section offers some policy implications.

2. Prior Studies

There is a rapidly growing empirical literature by economists dealing with the price sensitivity of consumption of illegal drugs. These demand studies primarily draw on illegal drug prices derived from local purchases made by drug enforcement agents while undercover. The studies typically combine these prices with self-reported measures of drug use from such national surveys as the NHSDA and Monitoring the Future (MTF). Grossman et al. (2002) provides a good review of this literature.

While the weight of the evidence from these studies suggests that cocaine and heroin use do respond negatively to price, there is little consensus about the magnitudes of the response. The illegal drug use indicators in these studies may be plagued by inaccuracies if self-reports are subject to response error, and such surveys also fail to capture many hardcore drug users. Recent studies have employed objective outcomes of drug use, related to urinalysis indicators derived from arrestees (Arrestee Drug Abuse Monitoring program) and drug-related hospital emergency department visits (Drug Abuse Warning Network).[8] Bypassing the under-reporting biases and being representative of more heavy users, these studies indicate low price-elasticity magnitudes: -0.15 for cocaine and -0.10 for heroin.

Given that higher drug prices reduce use, part of the decrease in use may result from individuals seeking treatment. Since more long-term measures of success are higher under treatment programs relative to no treatment, especially for heavy users, it is relevant to determine if there is a link between substance costs and treatment admissions. The above studies suggest that drug prices may play a role in motivating treatment, though this role is inferred indirectly from the effect of price on measures of use. We are aware of only one study to date that has directly examined the potential link between substance abuse treatment admissions and drug prices. Crane, Rivolo, and Comfort (1997) estimate a simple correlation of -0.39 between the cocaine price index and the fraction of treatment admissions related to cocaine from TEDS. This estimate does not control for time trends or other relevant factors that may affect both drug prices and admissions, and also fails to disentangle potentially opposing effects of drug prices on treatment. Conditional on drug use, higher drug prices would be expected to increase flows into treatment. Opposing this, however, is the unconditional effect of drug prices on treatment (which may be a proxy for the level of drug use). The combined effect will reflect both the pure inducement effect of

[8] See Dave (2008, 2006), Crane, Rivolo, and Comfort (1997), Caulkins (1996), and Hyatt and Rhodes (1995).

illicit drug costs on treatment as well as the negative own-price response of drug use. A priori, the net effect is ambiguously signed depending on the intensity of the individual components.

Evidence on the effectiveness of mental health parity legislation is mixed. McGuire and Montgomery (1982) find that the laws increase service use (as measured by hours of practice by fee-for-service psychiatrists and psychologists in 1978), though the estimates are imprecise. Frank (1985) similarly finds an increase in the number of visits to psychiatrists, based on a panel of states during the 1970s. More recent studies, however, differ in their findings. Klick and Markowitz (2006) employ state-level data from 1981 to 2000 and conclude that mental health mandates are not effective in reducing suicide rates. Based on individual-level data from the Healthcare for Communities survey, Pacula and Sturm (2000) also find that such legislation has not significantly increased utilization of mental health services. They surmise that the lack of an effect may be due to insurance displacement for high-risk individuals. Indeed, Sturm (2000) finds that individuals with a mental illness are more likely to lose insurance coverage in states with parity laws, though the estimates are small and insignificant.

Gruber (1994), conversely, shows that state mandates for certain health services including substance abuse and mental illness have no impact on the probability of coverage for an employee of a small firm. He finds some evidence, however, that state mandates to cover alcohol treatment may lower the probability that a small firm offers insurance. Gruber concludes that the mandates were ineffective as they were often lower than existing benefit levels offered by firms. Consistent with this explanation, the Substance Abuse and Mental Health Services Administration (SAMHSA 1999) reported that almost half of all eligible employers were already compliant with the federal Mental Health Parity Act of 1996 prior to becoming effective, and 68 percent of the plans saw no change in benefits as a result of the law. This, however, just points to the limited scope of the federal law and its various exemptions.

A SAMHSA report studied the experience of two insurers (Blue Cross/Blue Shield - BCBS and Kaiser/Community Health Plan) covering 80 percent of Vermont's privately insured population, subsequent to the state's parity law taking effect on January 1, 1998 (Hausman, 2003). Costs of providing mental health and substance abuse treatment increased from 2.3 percent of spending for all services to 2.47 percent for BCBS. Parity significantly increased the likelihood of insured individuals receiving mental health treatment, on the order of 18 to 24 percent; there was also a rise in the number of outpatient visits per use.

That evidence on the effects of insurance mandates on mental health services utilization is mixed is not to say that substance abuse and mental health treatment do not respond to prices or cost-sharing. Goodman et al. (1999) analyze an insurance claims database from self-insured employers and find that, conditional on treatment, substance abuse and mental health treatment respond to the price of care. Their results show that the magnitude of the price elasticity is directly related to the co-insurance rate. Thus, it still remains an open question whether mental health parity laws affect substance abuse treatment admissions, and the answer may hinge on whether the laws effectively expand access for individuals in need and facilitate significant cost-sharing. We are not aware of any large-scale, nationally-representative studies which have directly examined the link between mental health / substance abuse parity legislation and flows into treatment admissions.

III. Data

Treatment Episode Data Set (TEDS)

The empirical work in this study is based on substance abuse treatment admission flows derived from the Treatment Episode Data Set (TEDS). TEDS is an administrative data system designed to collect information on the number and characteristics of treatment admissions into private and public facilities receiving any public funding (including state agency funding and federal block grants). Data are collected by substance abuse agencies during the treatment intake interview with the client, and then forwarded to the Substance Abuse and Mental Health Services Administration (SAMHSA) for processing. TEDS covers about 85 percent of total admissions to eligible providers, which represents about 67 percent of the entire population of treatment admissions to all known providers. Due to the difficulties in obtaining data, states generally do not report information from purely private facilities that do not receive any state or public funds. Thus, while TEDS is not expected to represent a random subset of the *entire* population of treatment admissions, the population captured by TEDS is more likely to be low-income and low-education and is also more likely to be confronted with accessibility and cost-sharing issues relative to treatment admissions in purely private facilities.[9]

We employ data from 1992 to 2003 and restrict the analysis to clients who are 18 years of age and older, resulting in 18,870,164 substance abuse treatment admission records. For each admission, primary, secondary, and tertiary substances of abuse are observed along with client demographics, source of referral, prior history, insurance status, and payment source.[10] In 2003, alcohol was the most prevalent primary substance of abuse among admissions (44.4 %), followed by heroin (16.2 %), cocaine (14.9 %) and marijuana (11.3 %).

Tables 1a and 1b present the demographic composition of treatment admissions and drug use in 1992 and 2003. Data for drug use are based on self-reported past year illicit drug use from the National Surveys of Drug Use and Health (NSDUH) and cocaine and heroin-related hospital emergency department (ED) visits from the Drug Abuse Warning Network (DAWN).[11] Admissions are predominantly male, with a slight decline between 1992 and 2003 that also coincided with an increase in drug use among females. Treatment admissions are also primarily White, which remained relatively stable over time despite an increase in the prevalence of Whites among cocaine and heroin-related ED visits and a decline among past year illicit drug users; the percent of treatment admissions accounted by

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[9] With respect to ownership structure, about 59 percent of all treatment facilities are privately-operated but non-profit, about 27 percent are private for-profit, and the remainder are operated by the state, local or federal government (National Survey of Substance Abuse Treatment Services, 2006). About 81 percent of SA treatment admissions occur in TEDS-eligible facilities, with the remainder occurring in purely private facilities.

[10] Information on client insurance status and actual payment source, asked in 38 states, is available from the TEDS supplemental module. There are no systematic differences in admission characteristics between these 38 states and the full sample.

[11] The NSDUH (formerly National Household Surveys on Drug Abuse) is sponsored by the Substance Abuse and Mental Health Services Administration (SAMHSA), with the primary purpose of measuring the prevalence and correlates of drug use in the U.S. DAWN is an ongoing national probability survey also conducted by SAMHSA; it collects information on patients seeking hospital emergency department (ED) treatment related to their use of an illicit drug. To be included in DAWN, the patient must be age 6 years or older, be treated in the hospital's emergency department, and have a problem induced by or related to drug use, regardless of when the drug ingestion occurred. Eligible hospitals in the DAWN sample are non-Federal, short-stay general hospitals that have a 24-hour emergency department. Within each participating facility, a trained reporter,

Blacks, in comparison, declined from 27.2 to 24.7. Over this time period, there was also a rise in treatment admissions among young adults (ages 18-24) and older adults (ages 45-54). A progressively larger share of treatment admissions represented relatively educated individuals (65.4 % with a high school degree or above in 2003 versus 62.8 % in 1993). An opposite trend was however observed with respect to past year drug use (72.3 % of drug users had a high school degree or above in 1993 versus 68.5 % in 2003). Among past year drug users, approximately 74 percent had some form of health insurance in both 1993 and 2003. Over 21 percent of these individuals reported that they did not receive treatment due to affordability issues or because it was not covered by their health insurance plans. Compare this to SA treatment admissions, in which only about 12 percent of clients had private health insurance in 2003, with this share having declined from 16 percent in 1992. In contrast, the share of admissions with public insurance (Medicaid or Medicare) increased from 19 to 24 percent possibly reflecting in part the expansions in general Medicaid eligibility that occurred in the early to mid-1990s. The share of admissions among uninsured clients, however, remained unchanged.

Being privately insured does not necessarily mean that the client's treatment services are covered by insurance. In 2003, among privately insured clients, 46.7 percent paid mostly out-of-pocket (presumably because their plans do not offer commensurate coverage of SA treatment services); this share has almost doubled since 1992 (24.3 %). Among insured clients, private insurance covered the services for only about 43 percent of cases (down from 66 % in 1992). Thus, there are two noteworthy trends: first is the decline in private insurance status among treatment admissions, and second is the decline in coverage of treatment services conditional on insurance.

There has also been a slight decline in self-referrals, especially for heroin treatment admissions over this time period, and an increase in referrals from criminal justice sources (police officer, judge, probation official, or prosecutor). The decline in self-referrals may be indicative of payment and cost

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usually a nurse or a member of the ED or medical records staff, is responsible for reviewing medical charts for indications noted by the treating physician that the episode was drug related.

constraints.[12] This may be especially true for heroin admissions, where planned use of opioid treatment (medication-assisted therapy with methadone, LAAM, or buprenorphine) declined from 47 to 28 percent between 1992 and 2003. The mean cost per treatment admission with methadone use is significantly higher than without methadone use (SAMHSA, 2003). Public funding constraints may also direct states to selectively target special populations, including pregnant women, adolescents, and criminal justice referrals.[13]

There has also been a suggestive increase in supply constraints over the past 12 years. Both the number of facilities offering SA treatment as well the number of admissions per capita has remained relatively flat. The mean waiting period between request for service and actual admission (or first provision of clinical service) increased from about 5.5 to 7 days. The percent of admissions that had to wait for a week or more increased from 18 to 22.2.[14] Disparities in the demographic composition of heavy drug users (as inferred from ED visits) compared to treatment admissions suggests unequal propensity for seeking and obtaining treatment conditional on drug use, partly related to cost constraints and supply constraints.

Data Linked to TEDS

We matched the TEDS admission records to several additional variables based on year and state or city where the admission took place. The supplementary data include information on mental health parity laws, illicit drug prices, drug-related arrest rates, and state-level socio-economic conditions. Legislation regarding mental health parity laws is identified from the National Conference of State Legislatures' State Laws (Rickert and Ro, 2003). Two dichotomous indicators are constructed to capture whether a state in any given year has in place legislation mandating broad and limited insurance parity for the treatment of substance abuse disorders. The first indicator of broad parity relates to states which mandate

[12] Even though self-referrals declined, a greater portion of self-referrals was insured in 2003 versus 1992 suggesting a significant selection relating to cost-constraints and health coverage in terms of who seeks treatment.
[13] While we restrict the analysis to ages 18 and older, the share of adolescents (ages 11-17) has increased from 6.4 to 8.6 percent of all admissions.
[14] While the majority of clients enter treatment with no waiting time, this share has also declined from 66 to 58 percent.

comprehensive parity for the treatment of SA disorders and mental illnesses with few or no exceptions. These states mandate coverage of SA and mental health treatment on the same terms (including inpatient and outpatient visit limits, co-payments, deductibles, annual and lifetime limits) as applicable to other illnesses. In 2003, only ten states had legislated such broad parity.[15] The second measure reflects states which mandate mental health and SA treatment parity but in a limited sense; for these states, parity generally only applies to certain groups (ex: those with severe mental illness or state and local employees). In addition, some of these states only require employers to offer coverage and parity in one of their health plans (mandated offering) or require parity only if the plan offers any type of mental health service (mandated if offered). Other states mandate a minimum benefit that is less than equal to that for physical illnesses. In 2003, an additional eight states plus D.C. mandated substance abuse treatment parity, though they did so with several of these exceptions.[16]

Data on cocaine and heroin prices are computed from purchases made by undercover drug enforcement agents. Information on these purchases including cost, weight, and purity is recorded by the Drug Enforcement Agency (DEA) in their System to Retrieve Information from Drug Evidence (STRIDE). The advantage of STRIDE's transactions-level data is that they directly reflect prices on the street. These prices are expected to be relatively accurate because any unreasonable price offer by a DEA agent may raise suspicion on the dealer's part and endanger the agent. However, because the transactions are of varying size and quality, the cost of each drug must be standardized. Standardized prices of one pure gram of cocaine and heroin in a given metropolitan statistical area for a given year are derived in the following manner:

$$\text{(1)} \quad \text{Ln Cost}_{ijt} = \pi_0 + \pi_1 (\text{Ln Predicted Purity}_{ijt} + \text{Ln Weight}_{ijt}) + \pi_{2j} \sum \text{MSA}_j + \pi_{3t} \sum \text{Year}_t + \pi_{4jt} \sum \text{MSA}_j * \text{Year}_t + \upsilon_{ijt}$$

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15 The states with broad parity are CT, IN, KY, MD, MN, NC, RI, SC, VT, and WV.

16 The states with limited parity are CO, DE, GA, KS, MA, NH OH, and VA. It should be noted that while these measures of parity are broadly defined, there are some variations across states with respect to exemptions (ex: small businesses may be exempted; exemption if costs increase by 1-2 percent), coverage (ex: stronger provisions for state plans; coverage for co-occurring disorders), and policies affected (ex: group insurance, individual policies, HMO).

The subscripts denote the i^{th} transaction in the j^{th} MSA for year t. Cost refers to the total cost of the purchase, weight is the total gram weight of the purchase, and purity is the weight of the pure drug found in the purchase as a fraction of the total purchase weight. MSA and Year are dichotomous indicators for each while MSA*Year references interaction between the space and time indicators. Predicted Purity is obtained from a first-stage regression of actual purity on all of these other explanatory variables. The price of one pure gram of the drug in MSA j for year t is then imputed as:

(2) $\exp (\pi_0 + \pi_{2j} + \pi_{3t} + \pi_{4jt})$.

In the above procedure, purity is treated as endogenous because purchases may depend on expected rather than actual purity (Caulkins, 1994). Normally, in order to identify a two-stage model, instrumental variables that do not appear in equation (1) are required to predict purity. However, if a subset of the coefficients in (1) can be constrained, then such instrumental variables are not necessary. Specifically, theory suggests that the coefficient on predicted purity be constrained to equal the coefficient on weight in the second-stage regression.[17] As a sensitivity check, alternative price series based on purity treated as exogenous, and estimating (1) with the coefficients unconstrained, were also computed. There are no material changes in the results or conclusions. Dave (2008, 2006) and several other studies summarized in Grossman et al. (2002) use a similar methodology.

STRIDE data are available from 1974 to 2003, and all years are used to impute the price series for the periods represented in TEDS. There are 93,255 useable cocaine transactions and 41,114 heroin transactions.[18] The mean real price of one pure gram of cocaine over the 1992-2003 period is $131.21. The mean real heroin price is $606.53. Cocaine and heroin prices generally show a downward trend from

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[17] Equation (1) can be justified by defining the price of one pure gram of drug as:
Price = Cost / (Pure Quantity of Drug) $^{\pi 1}$, where pure quantity is purity times total weight. Here π_1 captures any non-linear effects of quantity on price, for example due to quantity discounts. In log-linear form, this is Log Price = Log Cost - π1 Log Purity - π1 Log Weight. It is assumed that the standardized price varies between cities and over time. Thus, Log Price = a + b MSA + c Year + d MSA*Year. Substitution of this expression in the log-linear formulation results in an estimable form, equation (1). Thus the coefficient on Log Purity can be restricted to equal the coefficient on Log Weight.

[18] In order to maximize the sample and cell sizes in subsequent estimation, heroin and cocaine prices that are missing in any given MSA for any given year, or for non-MSAs, are assigned the state-level price. Results are not sensitive to alternately omitting these values.

1992 to 2003 (Figure 4).[19] This coincided with a general increase in illicit drug use and drug-related hospital ED visits and a general decline in substance abuse treatment admissions, as shown in Figure 3.

Since the policy variables are measured at the geographic (state and metropolitan) level, additional locality-specific socioeconomic variables are included in all models to capture time-varying trends within areas. State personal income per capita is derived from the Bureau of Economic Analysis website, and total state population is obtained from the U.S. Bureau of Census. In order to capture local labor market conditions, the area-specific unemployment rate is also included in all models (obtained from the Bureau of Labor Statistics). Indicators of local enforcement efforts are further appended to admissions data. Variables measuring the total number of arrests in each city due to drug possession, drug sale or trafficking, and any drug-related violation are obtained from the FBI's Uniform Crime Reporting System. To separate out the effect of insurance parity legislation from other increases in state funding, all models also control for state substance abuse treatment and prevention block grants (obtained from the National Conference of State Legislatures). These are funds appropriated by Congress for states to use in treating substance abuse, and make up about 40 percent of public funds spent on prevention and treatment in the states. Means for all variables for the overall sample period (1992-2003) are presented in Table 2.

IV. Analytical Framework

Since illicit drugs are ultimately consumer goods, the analysis can be framed within the context of consumer theory. The probability that a given drug user would seek treatment is a function of the discounted net benefits of treatment. That is, it would be cost-effective for an individual to undergo substance abuse treatment if lifetime benefits exceeded the lifetime costs.

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[19] The decline in the real cocaine price has been attributed to the development of a production sector and the learning-by-doing that followed the reintroduction of cocaine into the U.S. market in the 1970s after prolonged absence. There was also vertical integration in the chain of distribution, which reduced the costs of retailing and wholesaling. Costs also declined from a shift to low-cost labor as unemployed residents of urban ghettos replaced the professionals who dealt drugs during the 1970s and 1980s. See Grossman et al. (2002). Heroin prices declined due to a shift in the heroin marketplace in the U.S. as drug cartels in Mexico and Colombia began to eclipse the Southeast Asian suppliers. Most of the heroin now entering the U.S. originates from these two countries. Consistent with these trends, prior studies have also shown that drug prices are significantly related to production costs (Kuziemko and Levitt, 2004; Basov, Jacobson, and Miron, 2001; Caulkins, 1995). Thus, prices vary strongly across localities and over time as a result of changes in distribution and shipping costs, labor costs, resources expended towards enforcement and apprehension of dealers, and severity of penalties.

(3) Prob(Treatment | Drug user) = f (Benefits - Costs)

Thus, factors which raise the benefits of treatment and/or lower the cost of treatment would increase flows into treatment admissions. Specifically, an increase in the monetary price of an illicit drug would raise the benefits of substance abuse treatment, ceteris paribus. Since illicit drug use, especially hardcore use, is price inelastic, higher monetary prices raise the monetary costs of drug consumption. As the mean drug price in a locality increases due to more stringent supply-side enforcement and interdiction, non-monetary costs for a given drug user may also multiply. In the face of an average price increase, the drug user also faces higher search costs in locating a potentially less costly supplier or traveling to another locality to secure a purchase. If supply-side interdictions that raise drug prices also result in a smaller pool of drug dealers and sellers, then search costs for the drug user further escalate. Searching for a new dealer may also worsen information asymmetry regarding quality and drug potency if the user has no prior experience with the dealer. Thus, the probability of seeking treatment may be greater when a given drug user is exposed to higher drug prices.

Similarly, cost-sharing through insurance would lower the cost of seeking treatment and make treatment a more attractive option for drug users, ceteris paribus. In this context, health insurance parity laws, by mandating mental health benefits to be commensurate with physical health benefits, may expand the coverage of substance abuse treatment and lower the out-of-pocket costs to the individual. Even if mental health parity laws do not explicitly mandate substance abuse treatment, they may still have a positive externality on such treatment due to the high comorbidity between mental disorders and substance abuse. Saffer and Dave (2005), for instance, show that individuals diagnosed with a mental illness in their lifetime are three times more likely to be cocaine users relative to individuals with no mental illnesses. Two-stage models further indicate that the higher prevalence of substance abuse among mentally-ill individuals at least partially reflects a causal channel from mental illness to substance abuse. This is consistent with mentally-ill individuals using psychoactive substances for self-medication. Thus, treatment for the underlying mental illness would raise the marginal product of substance abuse treatment due to the comorbid pathology. Any policy that effectively reduces the cost of psychiatric treatment would therefore have a positive impact on substance abuse treatment.[20]

In studying the effects of state parity legislation on SA treatment admissions, we proceed in two steps. First, we investigate whether the enactment of insurance parity increased the total number of treatment admissions in the state.

(4) $T_{st} = E_{st}\ exp\ (\lambda_0 + \lambda_1 L_{st} + Z_{st}\,\Omega + \upsilon_s + \tau_t + \omega_{st})$

Equation (4) posits that the total number of SA treatment admissions for state *s* in year *t* is a function of parity laws (*L*), a vector of state-varying characteristics such as economic conditions and SA-related funding (*Z*), and a stochastic disturbance (ω). All specifications control for state (υ) and year (τ) fixed effects, which account for unobserved time-invariant state heterogeneity and overall trends. Exposure for each unit is represented by E_{st} , which can be proxied by state population.[21] We choose to estimate this specification using a Poisson regression model for two reasons. First, the discrete nature of the outcome variable as a count of admissions makes the Poisson probability distribution especially suitable. Second, the Poisson framework does not suffer from the "incidental parameters" problem and can accommodate fixed effects well; both the conditional and unconditional likelihood maximization yield consistent and identical parameter estimates (Cameron and Trivedi, 1998). Since the Poisson framework implicitly assumes that the mean of each count (for state *s* and year *t*) is equal to its variance, we adjust all standard errors for over-dispersion as described in Wooldridge (2001).

Estimates from equation (4) will inform on whether comprehensive SA treatment parity increases flows into treatment facilities. Since, such state legislation is hypothesized to work through cost-sharing

[20] This characterization of the drug user as someone who responds to incentives and variations in costs and benefits is borne out in the literature. Studies have shown that drug consumption does respond negatively to monetary prices and the probability of arrest (Grossman et al. 2002, Dave 2006). Saffer and Dave (2005) analyzed the demand for addictive substances among individuals with mental disorders, a sub-population that may be most likely to abstain from rational decision-making. However, their study further confirms that even mentally-ill individuals cut back on their alcohol use, cigarette smoking, and cocaine use when monetary prices rise. Also see Becker, Grossman, and Murphy (1991) for an analysis of the drug user as a rational, lifetime utility maximizing agent.

[21] Specifying state population as the exposure constrains the coefficient of the natural log of population to one in the Poisson framework. We estimate models by including population as a covariate with its coefficient free-varying since state population may also proxy for the other state differences. Results are robust to both specifications.

and coverage of SA and mental health treatment, we further investigate whether the parity mandates affected the probability that a treatment admission is insured versus uninsured.[22]

(5) $C_{ist} = \beta_0 + \beta_1 L_{st} + X_{ist}\,\Gamma + Z_{st}\,\Pi + \upsilon_s + \tau_t + \varepsilon_{ist}$

In the above specification, *C* represents a coverage indicator for whether the i^{th} SA treatment admission, occurring in state *s* and year *t*, is privately-insured (and in alternative models, uninsured or publicly insured). Equation (5) postulates that this insurance status is a function of state regulations regarding parity in mental and physical health insurance (*L*), a vector of admission-specific characteristics such as the client's demographic and employment measures (*X*), a vector of state-specific factors including the total number of treatment admissions occurring in the state along with measures of the state's economic activity (*Z*), and a stochastic admission-specific disturbance (ε). Unmeasured time-invariant, state-specific characteristics (υ) and overall trends (τ) are accounted for by the inclusion state fixed effects and year fixed effects, respectively. The key parameter of interest is β_1, which represents the marginal effect of the state mandate on the insurance status of treatment admissions. This effect is identified through differences in the timing of enactment across states.

Using a similar framework, we explore how substance prices specifically affect treatment admissions related to cocaine and heroin.

(6) $T_{ist\,|\,\text{Cocaine / Heroin}} = \alpha_0 + \alpha_1 P_{st} + X_{ist}\,\Lambda + Z_{st}\,\Phi + \upsilon_s + \tau_t + \eta_{ist}$

Equation (6) is the estimable version of the model derived from two component behavioral frameworks.

(6a) Treatment (T) = f (Substance Use, Substance Price, X, Z; η)

(6b) Substance Use (D) = g (Substance Price, X, Z; η)

Treatment is conditional on substance use (including intensity, frequency, and onset), price of the illicit drugs, and a vector of other individual and locality-specific characteristics, which may include client demographics and aspects of the treatment facility including cost of treatment; this is stated in equation

[22] For computing convenience, models are estimated for a 35 percent random sample which ranges from 649,237 to 5,964,240 observations. Results are virtually identical to sensitivity analyses on multiple samples. Due to large sample sizes, we estimate and present results from linear probability models. Standard errors are adjusted for arbitrary correlation within state-year cells.

(6a). Equation (6b) is the consumer demand for illicit substances, which also depends on drug prices and individual and area-specific factors. Substituting the demand paradigm into (6a) and linearizing the equation results in the estimable form noted in (6).

One of the key policy-relevant parameters in equation (6) is α_1, the effect of changes in the illicit drug price on the demand for treatment. However, following from (6a) and (6b), this estimate represents a composite of two counteracting effects, as illustrated by the following decomposition.

$$(7) \qquad \frac{dT}{dP} = \left(\frac{\partial T}{\partial D}\right)\left(\frac{\partial D}{\partial P}\right) + \left(\frac{\partial T}{\partial P}\right)$$

An increase in the price of an illicit drug may motivate an increase in the demand for treatment admissions as it becomes more difficult and costly for users to sustain their drug consumption. This is the pure inducement effect of drug prices on treatment and is represented by the second term in the above identity ($\partial T / \partial P$), which is non-negative. However, countermanding this is a statistical endogeneity issue. When drug prices are higher in a given city, there is reduced drug use ($\partial D / \partial P < 0$). Fewer drug users or lower levels of drug use, in a statistical sense, lead to fewer treatment admissions ($\partial T / \partial D > 0$) in that locality. Thus, the first product term above is negatively signed. The magnitude of the first term depends on the demand price elasticity (especially for heavy use or among hardcore users) and the statistical correlation between drug use and treatment admissions. A priori, α_1 is therefore ambiguously signed, though equation (7) may be calibrated with prior estimates of the own-price elasticity of demand from the literature to inform on whether there is evidence of any substantially large inducement effect on treatment.

V. Results

Table 3 presents estimates of the Poisson model specified in equation (4). The first column shows that broad parity for substance abuse treatment significantly affects total flows into treatment admissions. Specifically, states which enact broad SA treatment parity see a 7.8 percent increase in total treatment admissions. Admissions are quadratic in age, increasing up to age 32 and then declining subsequently.

States which have higher treatment admissions also tend to have a higher prevalence of admissions which are male, non-White, and educated. Since the enactment of parity laws may be confounded with other state-varying factors, the specification in column 2 controls for state personal income per capita and the state unemployment rate. Funding from the federal block grant is also included in order to disentangle the effect of the parity legislation from funding changes directed at SA treatment and prevention. The estimate of broad parity remains robust to these controls.

If parity legislation has an effect on treatment admissions through cost-sharing, then this would most likely be realized for admissions which are self-referred. Individuals with SA problems would be more motivated to seek treatment if the services are covered under their health plans. Specification 3 therefore relates broad parity to the number of self-referred admissions. As expected, the marginal effect of the parity legislation increases in magnitude by about a third, suggesting that such laws increase the number of self-referrals by 11.7 percent. Specifications 4-6 analyze the impact of limited SA parity legislation, which is less comprehensive in scope and usually accompanied by exclusions. Such laws do not significantly increase treatment admissions. State SA funding (from federal block grants) has a positive effect on total treatment admissions; an increase in funding of ten million (which is about 16 % relative to the sample mean) would raise admissions by about 6 percent. Such funding usually goes towards providing subsidized or free care, and in the long-term, towards easing capacity constraints. Thus, they do not have any significant contemporaneous impact on self-referred admissions.

It should be noted that the reported effect magnitudes of the parity legislation are not substantial since they represent the impact of a 100 percent increase in the probability of enacting broad parity, which is about 3.4 times the observed standard deviation in these laws. Thus, a one standard deviation increase in the probability of enacting broad parity would raise total admissions by about 2.6 percent and self-referred admissions by about 3.5 percent.[23]

[23] Goodman et al. (1999) estimate an average out-patient treatment demand elasticity of approximately -0.43 and an average inpatient treatment demand elasticity of -1.14 (evaluated at a 50% coinsurance rate), based on a claims database. In their study 25 (50) percent of the increased inpatient (outpatient) usage attributable to fractional coinsurance comes from an increased

Since the most likely channel through which parity mandates affect treatment is through individual coverage, we investigate the plausibility of the above effects by analyzing whether the laws affected the observed coverage of treatment admissions.[24] Table 4 presents the results based on estimation of equation (5). The first specification indicates that states which mandate that substance abuse disorders be covered at the same terms as other ailments have a 3.1 percentage point higher probability that the treatment admission is privately insured after enacting the law, relative to states that do not offer such parity.

While SA parity legislation is likely to affect employed individuals or their spouses and dependents who have some form of health insurance, public funding is likely to target more vulnerable populations at risk of being on public support. Thus, crowd-out of private for public coverage is not a significant concern. Nevertheless, the possibility remains that states may be relying on parity legislation as a substitute for public funding or public coverage of SA treatment. Specification 2 suggests that this is not the case; among states which enacted broad SA parity, public insurance coverage of treatment admissions actually increased. The combined increase in private and public coverage of SA admissions serves to reduce the probability that an admission is uninsured by 7.4 percentage points (specification 3).

That broad SA parity raises the probability of a publicly-insured admission suggests that states were increasing funding efforts to treat and prevent SA problems over the sample period. SA funding through block grants was increasing at an average annual rate of about five percent. General expansions in Medicaid eligibility were also under way, reflected in the increase in the prevalence of public insurance among treatment clients (Table 1a). To the extent that these policies also coincided with the enactment of parity legislation, the estimate of the net effect of broad parity on uninsured admissions would be biased upwards (in absolute magnitude). Specifications 4-6 correct for this confounding by adding in a vector of

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number of users. In TEDS, about 40 percent of admissions are inpatient care and the remainder represents outpatient clients. Assuming a mean coinsurance rate for all health services of 20 percent, comprehensive SA parity would reduce an individual's price of treatment by 80 percent. Based on the mean price response from Goodman et al., SA parity would increase the number of inpatient and outpatient treatment users by 19.4 percent. Our estimates (7.8 - 8.9 %) are plausible in that they are less than half of the calibrated estimate. The conclusion offers some reasons for the muted effects.

[24] These models specifically utilize information on actual payment sources to determine the primary mode of payment for the treatment episode. Thus, a privately insured treatment admission represents an admission where the client had private health coverage and the coverage paid for the treatment service.

state funding-related covariates, including the SA treatment block grant and the percent of treatment admissions in the state covered by Medicaid and covered under other government payments. It is reassuring that, in specification 5, parity legislation no longer has any effect on the probability that the admission is publicly insured. Parity legislation should most plausibly affect private insurance coverage. Specifications 4 and 6 indeed suggest that broad SA parity raises the probability that an admission is privately insured and lowers the probability that an admission is uninsured by about 3.5 to 4 percentage points. The next two models control for a rich set of client-specific covariates including indicators for employment, marital status, and substances of abuse. The results remain relatively robust, though the effect sizes decline somewhat in magnitude; broad parity reduces the probability of an uninsured admission by about 2.4 percentage points.

This decline in the uninsured propensity, however, may not represent a net benefit or financial incentive to the individual if the increase in privately insured admissions (reduction in uninsured) is crowding out no-charge admissions. Parity laws would impart a financial incentive to seek treatment only through significant cost-sharing, that is if the individual would have had to pay out-of-pocket in the absence of the law. However, a significant portion (44 % in 2003) of admissions which are uninsured is not charged payments or falls under charity care. About half of the uninsured clients pay fully out-of-pocket. The 2.4 - 4.0 percentage-points reduction in the probability of uninsured is found to be roughly divided 40-60 between a decline in no-charge and a decline in self-pay admission probabilities.[25] That is, while comprehensive insurance mandates appear to reduced uninsured admissions, about 40 percent of the reduction would have received charity care through the facilities anyway. The remainder of the reduction in uninsured is matched by a decrease in admissions where the individual was fully responsible for payment (self-pay). Thus, the net effect of broad parity on the probability that a formerly self-paying admission is now covered by private insurance is about 1.4 to 2.4 percentage points. This is the relevant

[25] Results (not reported in the tables) are based on models for dichotomous indicators showing whether the admission was self-pay and no-charge. Reduced sample sizes for detailed payment sources make these estimates more imprecise (p-values between 0.10 and 0.20).

impact to consider since it represents a pure financial incentive for individuals to seek treatment who otherwise may find it inaccessible due to out-of-pocket costs. Evaluated at the sample prevalence of uninsured clients, this translates into an effect size of about 3 - 5 percent. The small magnitudes are consistent with the estimates from the aggregate models in Table 3.

The final two specifications in Table 4 consider the impact of limited SA treatment parity. The marginal effects on the probability of a privately insured admission and an uninsured admission are substantially lower relative to the effect of comprehensive parity. The estimates are not significant at conventional levels, and we cannot reject the null hypothesis of no effect. Since limited parity does not impart substantial cost-sharing and is not found to affect the coverage of treatment admissions, it is not surprising that the aggregate models also did not find significant increases in total treatment admissions related to limited parity.

The effects of the other demographic characteristics mimic the general composition of the population that is likely to have private health insurance (relative to public insurance or no insurance) -- white, male, and educated. There is a quadratic effect of age as private insurance propensity decreases up to age 29 or 30 and then rises subsequently.

Table 5 presents estimates of equation (6), in relation to whether the treatment admission involved cocaine as the primary, secondary, or tertiary substance of abuse. The monetary cost of cocaine has a significant negative impact on the probability of a cocaine treatment admission. The elasticity is estimated at around -0.07, suggesting that on the net drug use and treatment may be complementary rather than substitutes. However, from equation (7), this effect represents both the negative own-price effect for drug use and the incentive effect of higher prices on seeking treatment. Estimates of the price elasticity of demand for heavy users, based on objective indicators of cocaine use, center around -0.15 to -0.20 (Dave; 2006, 2008). Based on the NSDUH, only as much as 25 percent of substance abusers in need of treatment actually receive it. Thus, a crude calibration suggests that the pure incentive effect of higher drug prices in motivating treatment admissions is likely to be insubstantial and negligible.

The second column in Table 5 supplements the first model by adding in measures of client-specific characteristics and enforcement (proxied by drug-related arrests). States which have more illicit-drug related arrests have a higher probability of cocaine treatment admissions. This may reflect two channels. First, there may be a reverse causality issue -- if cocaine admissions are a reflection of the high level of drug use, then more resources may be devoted to enforcement in these areas. Alternately, part of this effect also reflects the synergies between enforcement, criminal justice spending and treatment. Individuals who come into contact with the criminal justice system may be diverted into treatment through alternative sentencing and drug courts. Indeed, enforcement has a somewhat larger effect on criminal justice referrals relative to self-referrals (models 5 and 4, respectively).

Effects of other demographic factors generally capture the characteristics of the population at risk of abusing cocaine: low-educated and non-White. One exception is with respect to gender; while males have a higher propensity for cocaine abuse, they are less likely to seek treatment as evidenced by the negative marginal effect for males, ceteris paribus (7 percentage point lower probability of cocaine treatment admission relative to females). Part of this effect may be related to a greater propensity for female drug abusers coming into contact with the criminal justice system to be diverted into treatment. About 19 percent of drug-related arrests are female; however, among criminal justice referrals into SA treatment admissions, over 30 percent are female. This relatively larger criminal justice-induced diversion of females into treatment is confirmed by the relatively larger negative marginal effect for males in specification 5. However, since males are also somewhat less likely to self-refer into treatment (specification 4), there appears to be some gender disparity in terms seeking treatment for cocaine abuse. There is a general increase in the probability of treatment up to age 35 and then a subsequent reduction. This is consistent with the age composition of cocaine ED visits in Table 1b, suggesting that the largest number of hardcore users are drawn from the 25-34 age group in 1994 and from the 35-44 age group in 2002. Estimates from the specification listed in the second column, controlling for a richer specification of covariates, suggest that most of the cocaine admissions are not-employed and also uninsured.

Specification 3 considers treatment admissions where cocaine is the primary and sole substance of abuse. The price elasticity is larger in magnitude, which is consistent with a larger own-price response on cocaine use when cocaine is only substance consumed. The next specification restricts the sample to self-referrals. If there was a strong incentive effect of higher cocaine prices in motivating individuals to seek treatment for their drug use, then we would expect the elasticity estimates for this group of self-referring admissions to decrease in magnitude towards zero. However, the estimate remains similar at around -0.07. This is consistent with the calibrations above, suggesting that there is not likely to be a substantial incentive effect operating through drug prices.

The final column restricts the sample to admissions where the individual was referred through the criminal justice system. The level of enforcement in the metro area continues to have a positive effect on cocaine admissions, though this effect is now somewhat diluted through the effect of drug prices. Since higher levels of enforcement lead to higher drug prices in the area, the cocaine price effect would also partially capture the positive effect of enforcement on criminal-justice initiated admissions. Thus, the marginal effect of the cocaine price is also somewhat reduced in magnitude.

Table 6 estimates similar specifications for treatment admissions where heroin is involved. The elasticity of treatment with respect to heroin price is in many cases positive and lower in absolute magnitude than that for cocaine. Note that this estimate still represents the two counteracting effects noted in equation (7). However, studies have shown that the own-price elasticity for heroin use, based on objective indicators for hardcore users, is among the lowest -- on the order or -0.05 --- and also lower than that for cocaine. Thus, ceteris paribus, the first term in equation (7) is less negative, making it more likely for the combined effect to be close to zero or even positive. Basic calibrations continue to suggest that even for heroin the incentive effect of heroin prices in inducing individuals to seek treatment is not likely to be substantial.

The probability of a heroin treatment admission increases up to age 42 and declines thereafter. Even though males are significantly more likely to use and abuse heroin, they have a lower probability (by 2 - 3 percentage points) of a heroin treatment admission. Non-Whites have a higher probability of a treatment admission for heroin, though in 2002 a larger proportion of hospital ED visits involving heroin occurred among Whites. Some of the higher prevalence of non-Whites in heroin treatment admissions occurs as a result of contact with the criminal justice system. For the overall sample and for self-referrals, heroin treatment admissions are most likely to be on public insurance; however, for criminal justice referrals, admissions are most likely to be uninsured. Similar to cocaine admissions, the level of enforcement continues to positively impact admissions.

VI. Discussion

The consensus in the prior literature indicates that substance abuse treatment is both efficacious and cost-effective relative to other drug-control alternatives. Furthermore, the gap between heavy drug use and treatment admissions has widened over the last decade, as drug use has trended upwards while treatment admissions have lagged behind. Thus, from a policy standpoint, it is integral to analyze the economic factors that impact flows into substance abuse treatment.

Results suggest that the pure incentive effect of drug prices in inducing individuals to enter treatment may not be substantial. This is consistent with prior studies that have shown very low own-price responses for heavy substance and alcohol use (Dave, 2008; Manning et al., 1995). That is, if the goal is to reduce heavy substance use or affect hardcore users, this is less likely to be achieved through further increases in monetary costs of the substances. However, it should be noted that synergies and linkages between enforcement, criminal justice contact, and treatment referrals through various sources preclude such a broad characterization. Enforcement-induced contact with the criminal justice system may provide opportunities to divert in-need populations into treatment and rehabilitation.

A significant portion of drug abusers cite cost and accessibility issues as a primary reason for forgoing treatment. Thus, even if higher drug prices have a potentially motivational effect on inducing an individual to seek treatment, there exist additional accessibility issues and cost barriers to obtaining treatment services. For instance, among privately insured individuals in 2006, treatment services were primarily paid out-of-pocket almost half the time; private insurance was the primary source of payment in only about 31 percent of the cases.

The importance of cost-sharing is highlighted by the analysis of state insurance parity legislation. The results indicate that laws which mandate broad parity for SA and mental health treatment are associated with an increase in the total number of treatment admissions, especially self-referred admissions. Such legislation also raises the probability that the admission is privately insured and conversely decreases the probability that the admission is uninsured. While there does not appear to be any crowding-out with respect to public insurance support, there is some crowd-out with respect to charity care and non-payment. Nevertheless, on the net, there is a 1.4 to 2.4 percentage point reduction in the probability of uninsured self-payer treatment admissions. These effects are confined to states which support broad and comprehensive parity. Limited parity does not appear to have any discernible positive impact on the number of treatment admissions or cost-sharing. While the effect magnitudes of broad parity are not substantial, this may reflect several underlying factors. First, parity legislation applies only to health insurance already offered and would most likely affect individuals who have some form of non-public coverage. Data from the NSDUH indicate that about 59 percent of the drug-abusing population has private health insurance compared to 72 percent of individuals who do not use drugs. Thus, the effectiveness of SA parity mandates may be limited in scope by relating to drug users with access to non-public coverage in the first place. Second, perhaps more relevant for this analysis, the limited effect sizes may also reflect supply and capacity constraints. Even if parity legislation induces demand for treatment by reducing costs among covered individuals, there may be some offset as the number of facilities have remained relatively constant over the past decade and waiting times have trended upwards.[26] This relatively inelastic supply of treatment suggests that our estimates of the effects of parity on treatment admissions and coverage incentives may be on the conservative side.

[26] This parallels the early experience of Massachusetts, where an increase in the insured population as a result of the health insurance mandates and other reforms has led to an increase in waiting times and unmet demand for primary care services due to restricted supply of primary care doctors.

Currently, only 18 states plus D.C. mandate any type of parity for substance abuse treatment, and only ten states mandate comprehensive parity, leaving significant potential to reduce chronic drug use and maximize long-term abstinence through more states adopting strong parity laws beyond the MHPA amendments.[27] Since parity legislation may not help to defray costs for all, policy interventions which subsidize treatment among uninsured users also has the potential to significantly provide treatment to those who need it but cite cost constraints as an impediment. However, such demand-focused interventions by themselves may likely have muted effects unless paired with policies which improve treatment supply and capacity.

[27] Studies have consistently shown that a popular argument against enacting such laws, namely an increase in health care costs, remains unfounded (Hausman, 2003; Sturm et al., 1999).

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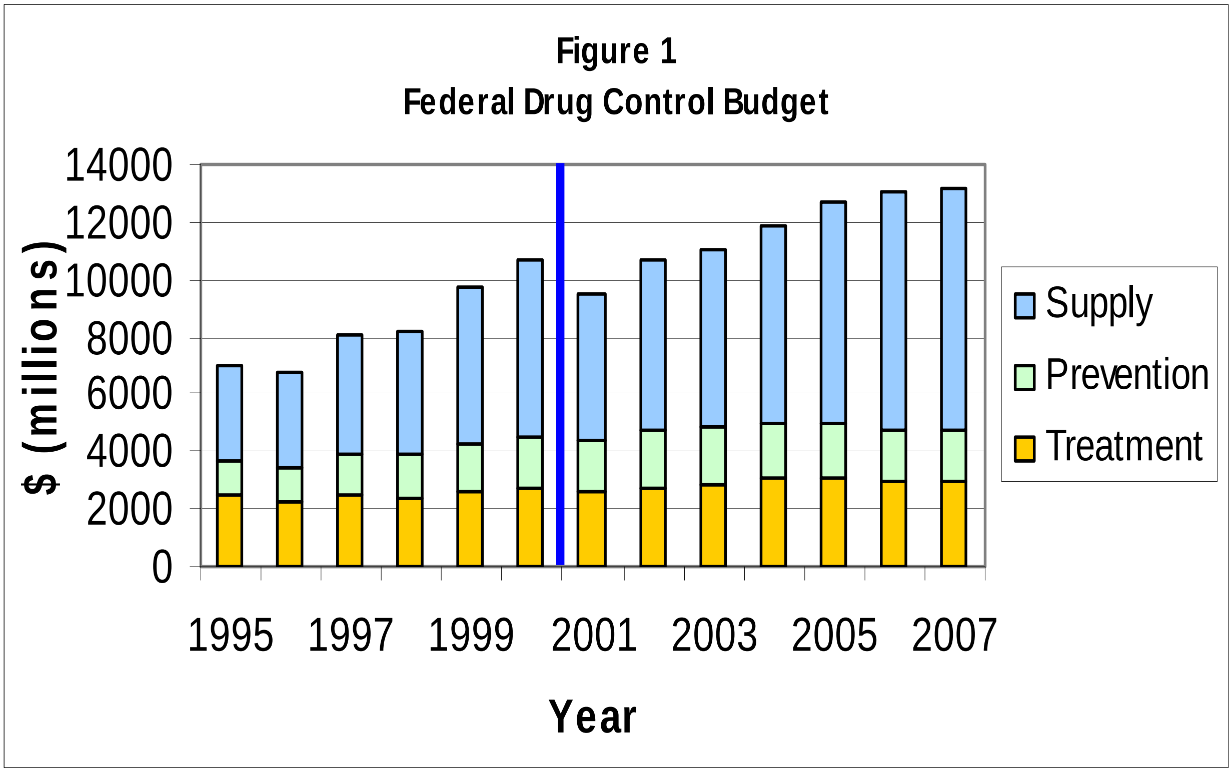
Figure 1
Federal Drug Control Budget
$ (millions)
14000
12000
10000
8000
6000
4000
2000
0
1995
1997
1999
2001
2003
2005
2007
Year
Supply
Prevention
Treatment

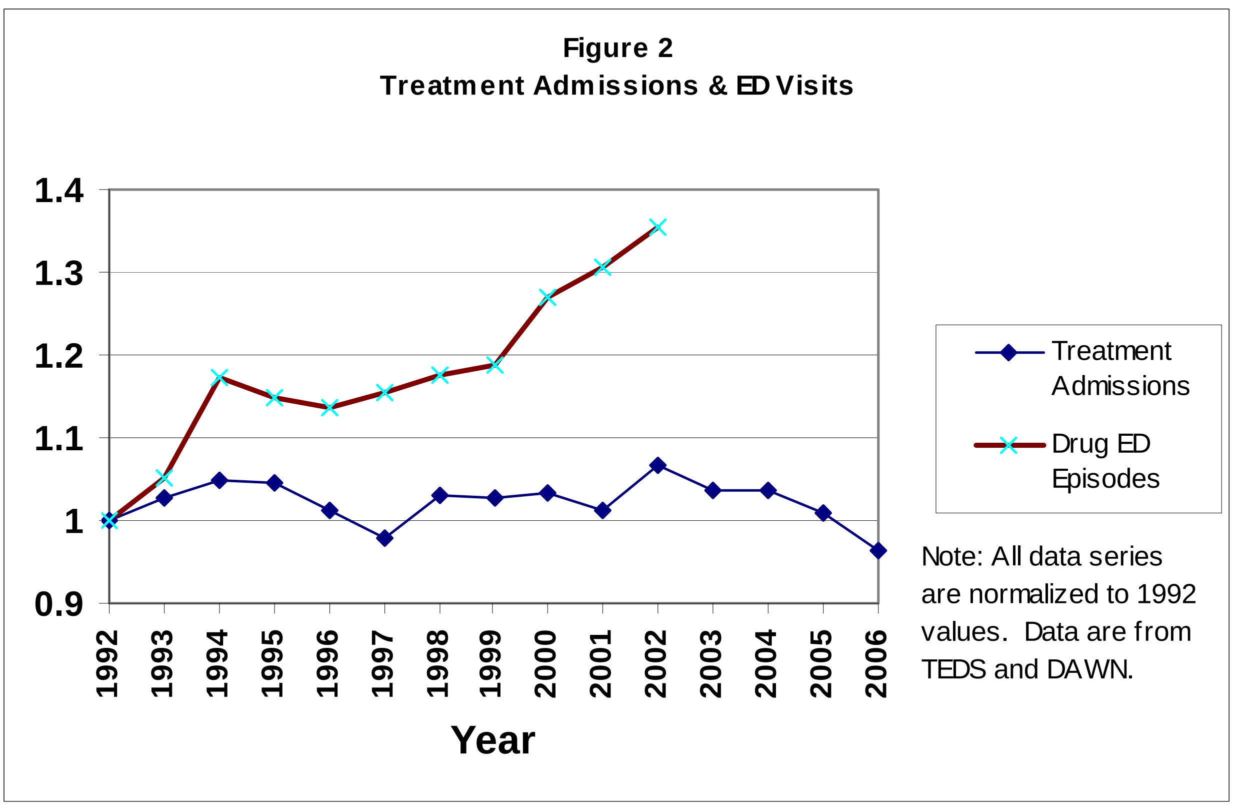
Figure 2
Treatment Admissions & ED Visits
1.4
1.3
1.2
1.1
1
0.9
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
Year
Treatment Admissions
Drug ED Episodes
Note: All data series are normalized to 1992 values. Data are from TEDS and DAWN.

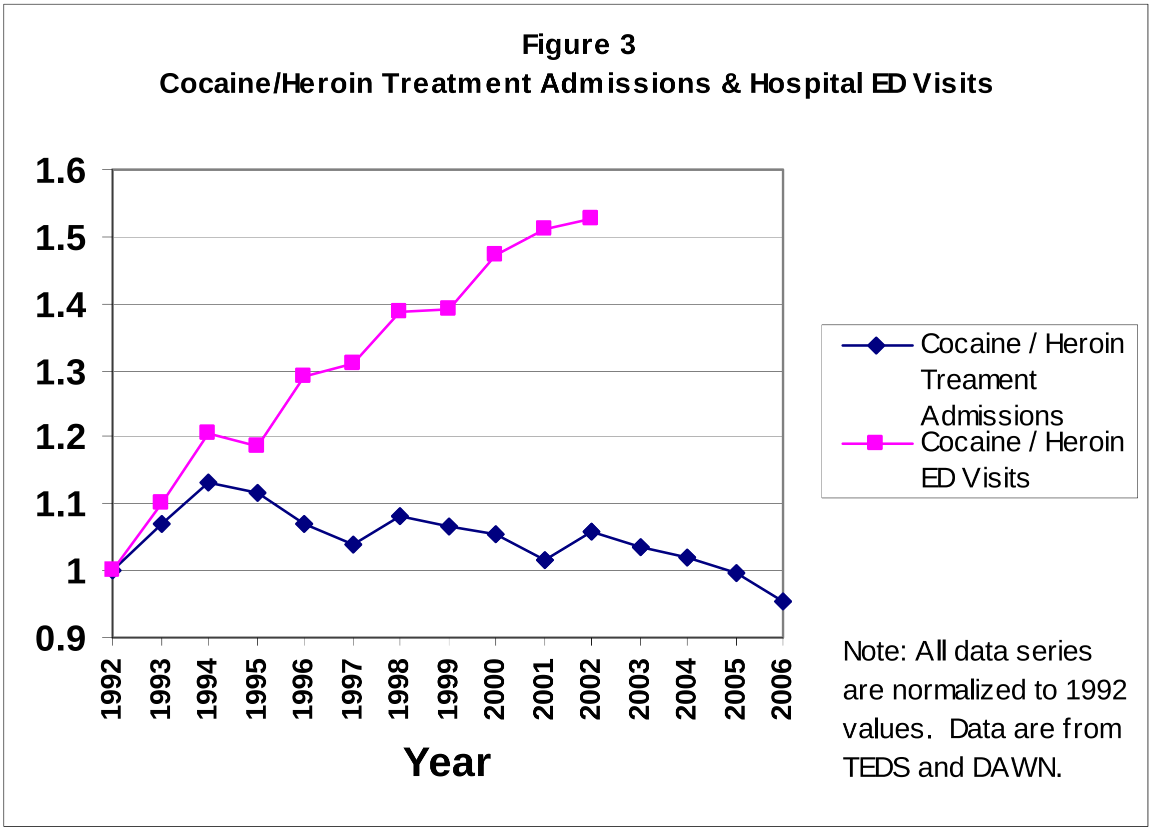
Figure 3
Cocaine/Heroin Treatment Admissions & Hospital ED Visits
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
Year
Cocaine / Heroin Treament Admissions
Cocaine / Heroin ED Visits
Note: All data series are normalized to 1992 values. Data are from TEDS and DAWN.

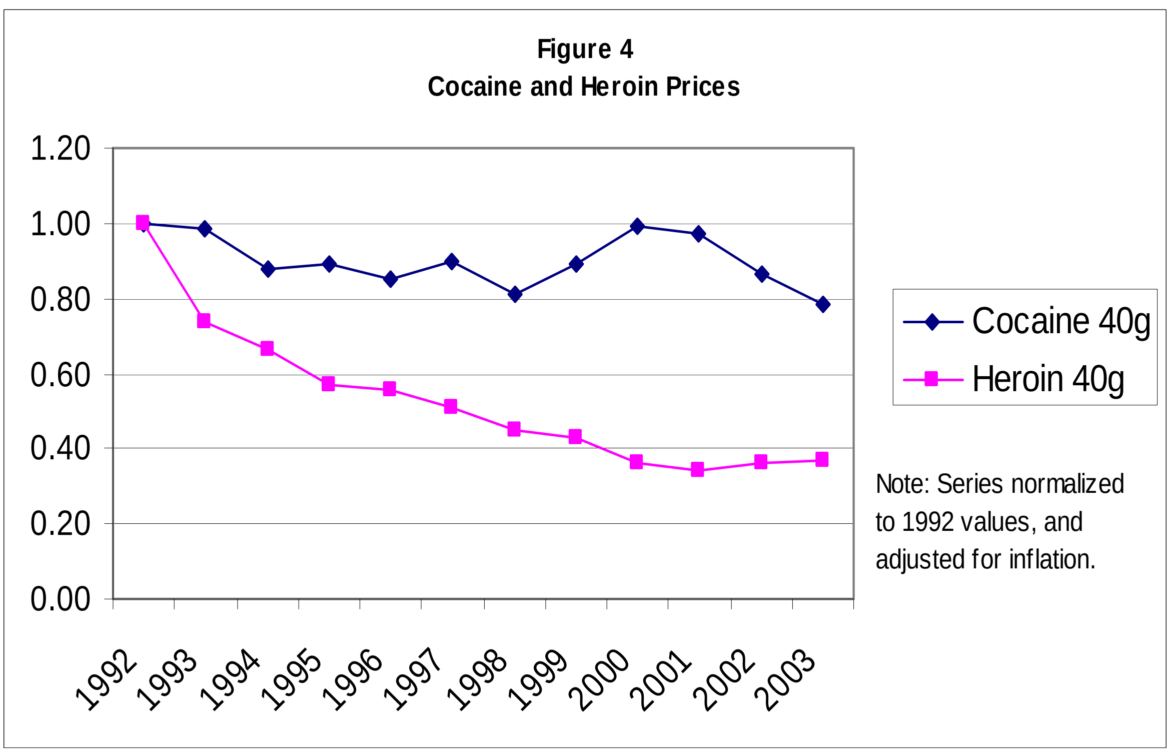
Figure 4
Cocaine and Heroin Prices
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
Cocaine 40g
Heroin 40g
Note: Series normalized to 1992 values, and adjusted for inflation.

Table 1a
Demographic Composition
Treatment Admissions (TEDS) [1]

Variable	All		Cocaine		Heroin	
	1992	2003	1992	2003	1992	2003
Male	72.6	69.1	66.6	65.2	67.1	68.3
White	61.8	62.2	41.8	45.5	47.4	52.0
Black	27.2	24.7	48.6	42.4	28.6	26.2
Ages 18-24	16.7	19.1	16.5	12.1	9.4	14.8
Ages 25-34	42.5	27.1	53.1	28.2	39.9	27.9
Ages 35-44	28.0	33.0	25.9	41.6	40.6	34.1
Ages 45-54	9.0	16.7	4.0	16.0	8.4	19.9
Employed Full-Time	27.9	22.4	18.9	15.0	14.8	12.0
Employed Part-Time	6.8	7.1	5.2	5.0	4.8	4.4
Unemployed	29.3	32.4	34.4	34.7	32.5	36.2
High School and above	62.8	65.4	60.7	63.1	59.8	61.8
Self Referral	36.6	35.7	40.5	39.3	62.7	56.3
Criminal Justice Referral	33.0	34.5	23.6	25.7	13.1	15.1
Health Care Referral	20.8	18.4	25.2	22.9	19.2	20.9
Private Health Insurance	15.8	11.7	10.7	8.8	8.3	10.1
Public Health Insurance	19.2	23.5	23.3	25.6	29.3	29.8
Uninsured	65.0	64.8	66.1	65.6	62.5	60.1
Payment Source - Private Insurance	9.5	7.2	7.0	5.8	5.0	5.7
Payment Source - Public Insurance	12.0	14.6	16.5	18.0	23.7	20.1
Payment Source - Self	44.1	39.5	35.2	32.6	29.0	30.4
Payment Source - No Charge / Other	34.4	38.6	41.3	43.6	42.3	43.8
No Prior Treatment Admissions	44.4	41.4	37.8	31.3	25.2	22.2
Days waiting to enter treatment [2]	5.5	6.9	4.9	5.7	5.9	6.4
Planned Opioid treatment	-	-	-	-	47.2	28.0
Observations	1,453,260	1,684,742	532,148	555,072	210,107	323,591

[1] Data are from the Treatment Episode Dataset. Cells represent percent of treatment admissions in each category, except where noted. Observations represent maximum sample size; for some variables, the sample size is less due to missing information. Cocaine and Heroin represent treatment admissions where the drug is mentioned as the first, second, or tertiary substance of abuse.
[2] Mean number of days between initial request for service and actual admission or provision of clinical service.

Table 1b
Demographic Composition
Drug Use (NSDUH and DAWN) [1]

Variable	Past Year Illicit Drug Use (NSDUH)		Cocaine ED Visits (DAWN)		Heroin ED Visits (DAWN)	
	1993	2003	1994	2002	1994	2002
Male	57.7	56.7	67.8	64.7	70.6	66.4
White	76.3	71.2	30.9	43.2	41.2	48.8
Black	11.4	12.1	58.3	43.3	42.7	35.1
Ages 18-24	-	-	15.2	13.4	10.3	16.2
Ages 25-34	-	-	44.9	28.6	34.2	26.4
Ages 35-44	-	-	30.3	37.6	39.4	32.2
Ages 45-54	-	-	6.7	16.2	13.6	20.3
Employed Full-Time	49.1	50.4	-	-	-	-
Employed Part-Time	14.1	17.4	-	-	-	-
Unemployed	8.7	7.3	-	-	-	-
High School and above	72.3	68.5	-	-	-	-
Health Insurance	73.5	73.7	-	-	-	-
Prevalence / Number [1]	11.8	14.8	143,337	199,198	63,158	93,519

1 Cells represent prevalence (percent) for past year illicit drug use from NSDUH, and total number of hospital emergency department (ED) mentions related to the specific illicit drug from DAWN.

Table 2

Sample Means - Treatment Episode Data Set (TEDS) & Merged Variables
1992 - 2003

Variable	Definition	Mean (Std. Deviation)
Cocaine Admission	Cocaine is mentioned as the first, second, or third substance of abuse related to the treatment admission	0.3526 (0.4778)
Heroin Admission	Heroin is mentioned as the first, second, or third substance of abuse related to the treatment admission	0.1823 (0.3861)
Age	Age of admission	34.8400 (9.4252)
Male	Client is male	0.7063 (0.4555)
White	Client is White	0.6096 (0.4878)
Black	Client is Black	0.2640 (0.4408)
Other Race	Client is of a race other than White or Black	0.1264 (0.3323)
Hispanic	Client is Hispanic	0.1219 (0.3271)
High School	Client is a high school graduate	0.6419 (0.4794)
College	Client is a college graduate	0.0450 (0.2072)
Employed Full-time	Client is employed full-time	0.2616 (0.4395)
Employed Part-time	Client is employed part-time	0.0682 (0.2521)
Substance Abuse Parity - Broad	State provides full or broad-based substance abuse treatment parity Source: National Conference of State Legislatures	0.0961 (0.2948)
Substance Abuse Parity - Limited	State provides limited substance abuse treatment parity Source: National Conference of State Legislatures	0.0808 (0.2725)
Cocaine Price	Price of one pure gram of cocaine in metro area of treatment admission, in thousands of dollars Source: STRIDE, DEA	0.1312 (0.0431)
Heroin Price	Price of one pure gram of heroin in metro area of treatment admission, in thousands of dollars Source: STRIDE, DEA	0.6065 (3.6366)
Private Insurance	Client has private health insurance	0.1294 (0.3356)
Public Insurance	Client has public health insurance, including Medicaid or Medicare	0.2181 (0.4130)
Uninsured	Client is uninsured	0.6525 (0.4762)
Payment Source - Private Insurance	Treatment is covered under private insurance	0.0797 (0.2708)
Payment Source - Public Insurance	Treatment is covered under public insurance	0.1347 (0.3414)
Payment Source - No Insurance	Treatment is not covered under any insurance	0.7856 (0.4104)
Payment Source - Self-Pay	Primary source of payment for the treatment admission is self-pay	0.4131 (0.4924)
Payment Source - Other	Treatment service is provided at no-charge or covered through other government payments	0.3725 (0.4835)
Drug-related Arrests	Total drug related arrests for possession or sale in metro area of treatment admission, in thousands Source: Uniform Crime Reports, FBI	21.19 (33.98)

Referral Source - Individual / Self	Client was referred to substance abuse treatment through self, family or friend	0.3660 (0.4817)
Referral Source - Criminal Justice	Client was referred to substance abuse treatment through any police official, judge, prosecutor, probation officer, or other person affiliated with a Federal, State, or county judicial system	0.3316 (0.4708)
State Treatment Admissions	Total annual substance-abuse treatment admissions in state	97036.82 (90880.94)
State Population	State population, in millions Source: U.S. Census Bureau	11.54 (9.24)
State Personal Income	State personal income per capita, in thousands Source: U.S. Bureau of Labor Statistics	27.55 (5.37)
State Unemployment	State unemployment rate, in percentage points Source: U.S. Bureau of Labor Statistics	5.49 (1.48)
State SA Block Grant	State substance abuse treatment block grant, in millions of dollars Source: National Conference of State Legislatures	60.88 (57.52)
Observations [1]	Total number of observations in the analysis sample	6,632,886

[1] For computing convenience, analyses are performed on a 35 percent random sample. There were a total of 18,870,164 substance-abuse treatment admissions in TEDS between 1992 and 2003. Sample size listed is the maximum number of observations. For some variables (mostly, insurance and payment source), sample sizes are smaller due to missing records.

Table 3

State Health Insurance Parity and Aggregate SA Treatment Admissions [1]

Poisson Regression Models

Model	1	2	3	4	5	6
Dependent Variable	Total SA Treatment Admissions	Total SA Treatment Admissions	Self-Referred SA Treatment Admissions	Total SA Treatment Admissions	Total SA Treatment Admissions	Self-Referred SA Treatment Admissions
Substance Abuse Parity - Broad	0.0783* (0.0435)	0.0889** (0.0428)	0.1170** (0.0527)	–	–	–
Substance Abuse Parity - Limited	–	–	–	-0.0162 (0.0594)	-0.0045 (0.0604)	0.0341 (0.0616)
Age	-0.6541* (0.3498)	-0.7382** (0.3550)	-0.7309** (0.3598)	-0.6598* (0.3537)	-0.7227** (0.3559)	-0.7212** (0.3621)
Age-squared	0.0101** (0.0049)	0.0114** (0.0050)	0.0128** (0.0050)	0.0102** (0.0050)	0.0111** (0.0050)	0.0125** (0.0050)
Male	0.0805 (0.5825)	0.0199 (0.5890)	-2.4223*** (0.4207)	0.0871 (0.5971)	-0.0030 (0.5959)	-2.4943*** (0.4258)
Black	1.6157*** (0.5088)	1.4216*** (0.5048)	1.7310*** (0.5142)	1.5518*** (0.5186)	1.3801*** (0.5177)	1.7766*** (0.5207)
Other Race	0.5187* (0.2780)	0.2628 (0.2925)	-0.3278 (0.4499)	0.5230 (0.3216)	0.2888 (0.3289)	-0.2466 (0.4727)
Hispanic	-0.0353 (0.1865)	-0.0584 (0.1883)	-0.0253 (0.1669)	-0.0024 (0.1819)	-0.0271 (0.1864)	0.0203 (0.1652)
High School	0.5545 (0.4946)	0.5710 (0.4974)	1.3609** (0.5947)	0.5840 (0.5008)	0.5998 (0.5030)	1.3628** (0.6005)
College	3.4290*** (0.9666)	3.2579*** (0.9656)	1.9457** (0.9914)	3.3132*** (0.9404)	3.1188*** (0.9371)	1.8206* (0.9609)
State Population	-0.0296 (0.0195)	-0.1556*** (0.0449)	-0.1155** (0.0545)	-0.0351* (0.0194)	-0.1564*** (0.0450)	-0.1152** (0.0544)
State SA Block Grant	–	0.0061*** (0.0020)	0.0006 (0.0024)	–	0.0058*** (0.0020)	0.0003 (0.0024)
State Covariates [2]	No	Yes	Yes	No	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared [3]	0.973	0.973	0.975	0.973	0.973	0.975
Observations	562	562	555	562	562	555

[1] Dependent variable represents a count of the number of SA treatment admissions in the states. Data are aggregated by state and year. Coefficient estimates from Poisson regression models are presented. Standard errors are adjusted for over-dispersion and reported in parentheses. Significance is denoted as follows: *** p≤0.01, ** 0.01<p≤0.05, * 0.05<p≤0.10.

[2] Vector includes state personal income and state unemployment rate.

[3] Pseudo R-squared represents one minus the ratio of the log-likelihoods for the full model versus the intercept-only model.

Table 4

Insurance Status of Treatment Admissions [1]

Linear Probability Models

Model	1	2	3	4	5	6	7	8	9	10
Dependent Variable	Admission Privately Insured	Admission Publicly Insured	Admission Uninsured	Admission Privately Insured	Admission Publicly Insured	Admission Uninsured	Admission Privately Insured	Admission Uninsured	Admission Privately Insured	Admission Uninsured
Substance Abuse Parity - Broad	0.0308*** (0.0105)	0.0427*** (0.0123)	-0.0735*** (0.0175)	0.0356*** (0.0110)	0.0047 (0.0037)	-0.0403*** (0.0111)	0.0187** (0.0083)	-0.0241*** (0.0084)	–	–
Substance Abuse Parity - Limited	–	–	–	–	–	–	–	–	0.0121 (0.0099)	-0.0161 (0.0112)
Age	-0.0043*** (0.0005)	0.0014*** (0.0005)	0.0029*** (0.0006)	-0.0043*** (0.0005)	0.0013*** (0.0005)	0.0030*** (0.0005)	-0.0078** (0.0007)	0.0036*** (0.0007)	-0.0043*** (0.0005)	0.0030*** (0.0005)
Age-squared	0.0001*** (0.00001)	0.00001 (0.00001)	-0.0001*** (0.00001)	0.0001*** (0.00001)	0.00001 (0.00001)	-0.0001*** (0.00001)	0.0001** (0.00001)	-0.0001*** (0.00001)	0.0001*** (0.00001)	-0.0001*** (0.00001)
Male	0.0177*** (0.0028)	-0.1400*** (0.0055)	0.1223*** (0.0050)	0.0176*** (0.0028)	-0.1392*** (0.0055)	0.1217*** (0.0050)	-0.0029 (0.0025)	0.1192*** (0.0058)	0.0175*** (0.0028)	0.1217*** (0.0050)
Black	-0.0518*** (0.0046)	0.0700*** (0.0055)	-0.0182*** (0.0049)	-0.0516*** (0.0046)	0.0680*** (0.0052)	-0.0164*** (0.0045)	-0.0284** (0.0032)	-0.0224*** (0.0036)	-0.0516*** (0.0046)	-0.0165*** (0.0045)
Other Race	-0.0075** (0.0030)	0.0076** (0.0030)	-0.0001 (0.0037)	-0.0077*** (0.0029)	0.0053** (0.0027)	0.0024 (0.0037)	-0.0040* (0.0023)	0.0015 (0.0036)	-0.0070** (0.0028)	0.0016 (0.0036)
Hispanic	-0.0237*** (0.0051)	0.0072*** (0.0027)	0.0165*** (0.0040)	-0.0236*** (0.0051)	0.0089*** (0.0025)	0.0147*** (0.0040)	-0.0242** (0.0033)	0.0152*** (0.0038)	-0.0239*** (0.0050)	0.0150*** (0.0040)
High School	0.0379*** (0.0027)	-0.0509*** (0.0025)	0.0130*** (0.0023)	0.0379*** (0.0027)	-0.0498*** (0.0024)	0.0120*** (0.0022)	0.0277** (0.0018)	0.0101*** (0.0018)	0.0379*** (0.0027)	0.0119*** (0.0022)
College	0.0669*** (0.0055)	-0.0375*** (0.0034)	-0.0294*** (0.0039)	0.0669*** (0.0055)	-0.0372*** (0.0034)	-0.0297*** (0.0039)	0.0531** (0.0048)	-0.0289*** (0.0034)	0.0670*** (0.0055)	-0.0298*** (0.0039)
State Covariates [2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Funding Covariates [3]	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended Individual Covariates [4]	No	No	No	No	No	No	Yes	Yes	No	No
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.079	0.198	0.227	0.079	0.208	0.233	0.133	0.238	0.079	0.233
Observations [5]	1,780,776	1,780,776	1,780,776	1,780,776	1,780,776	1,780,776	1,625,794	1,625,794	1,780,776	1,780,776

[1] Dependent variable represents a dichotomous indicator of whether a substance abuse treatment admission is privately insured, publicly insured, or uninsured. Estimates from linear probability models are presented. Standard errors are adjusted for arbitrary correlation within state-year cells and reported in parentheses. Significance is denoted as follows: *** $p \leq 0.01$, ** $0.01 < p \leq 0.05$, * $0.05 < p \leq 0.10$.

[2] Vector includes total number of substance abuse treatment admissions in the state, state-level personal income per capita, state unemployment rate, and state population.

[3] Vector includes state substance abuse treatment block grant, percent of treatment admissions in state covered by Medicaid, and percent of treatment admissions in state covered by state funds including public insurance and other state payments to SA facilities.

[4] Vector includes indicators for full-time and part-time employment, marital status, number of substances of abuse, and indicators for whether alcohol, cocaine, heroin, and marijuana were cited as the primary, secondary, or tertiary substances of abuse.

[5] For computing convenience, analyses are performed on a 35 percent random sample.

Table 5
Cocaine Treatment Admission [1]
Linear Probability Models

Sample	All			Self Referrals	Criminal Justice Referrals
Model	1	2	3	4	5
Dependent Variable	Cocaine Admission	Cocaine Admission	Primary Cocaine Admission	Cocaine Admission	Cocaine Admission
Cocaine Price	-0.2840*** (0.0382) [ε = -0.102]	-0.2079*** (0.0475) [ε = -0.072]	-0.1445*** (0.0447) [ε = -0.165]	-0.2107*** (0.0682) [ε = -0.068]	-0.1713*** (0.0500) [ε = -0.077]
Age	0.0455*** (0.0015)	0.0479*** (0.0014)	0.0183*** (0.0013)	0.0336*** (0.0013)	0.0495*** (0.0015)
Age-squared	-0.0007*** (0.00002)	-0.0007*** (0.00002)	-0.0003*** (0.00002)	-0.0006*** (0.00002)	-0.0007*** (0.00002)
Male	-0.0700*** (0.0029)	-0.0703*** (0.0026)	-0.0692*** (0.0028)	-0.0336*** (0.0037)	-0.0936*** (0.0036)
Black	0.3268*** (0.0063)	0.2825*** (0.0069)	0.2230*** (0.0095)	0.3124*** (0.0084)	0.2167*** (0.0084)
Other Race	0.0134*** (0.0035)	0.0012 (0.0056)	0.0021 (0.0054)	0.0089 (0.0076)	-0.0063 (0.0080)
Hispanic	0.0469*** (0.0037)	0.0318*** (0.0043)	0.0040 (0.0041)	0.0323*** (0.0058)	0.0228*** (0.0057)
High School	-0.0052*** (0.0012)	-0.0008 (0.0015)	0.0084*** (0.0014)	-0.0067*** (0.0020)	-0.0078*** (0.0019)
College	-0.0395*** (0.0033)	-0.0394*** (0.0029)	0.0042*** (0.0014)	-0.0371*** (0.0032)	-0.0452*** (0.0041)
Full-time Employed	_	-0.1116*** (0.0037)	-0.0503*** (0.0034)	-0.0581*** (0.0044)	-0.1214*** (0.0054)
Part-time Employed	_	-0.0880*** (0.0031)	-0.0484*** (0.0030)	-0.0489*** (0.0041)	-0.0918*** (0.0044)
Private Insurance	_	-0.0407*** (0.0029)	-0.0090*** (0.0023)	-0.0394*** (0.0044)	-0.0830*** (0.0035)
Public Insurance	_	-0.0090*** (0.0032)	-0.0084*** (0.0025)	-0.0253*** (0.0044)	-0.0082** (0.0041)
Drug-related Arrests	_	0.0012*** (0.0002)	0.0004** (0.0002)	0.0005** (0.0003)	0.0007*** (0.0002)
State Covariates [2]	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
State Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.169	0.172	0.164	0.155	0.171
Observations [3]	5,964,240	2,056,786	947,984	745,524	702,395

[1] Cocaine Admission represents a dichotomous indicator of whether cocaine is mentioned as a first, second, or third substance of abuse related to the treatment admission. Primary Cocaine Admission refers to a dichotomous indicator for whether cocaine is the primary and only substance of abuse. Estimates from linear probability models are presented. Standard errors are adjusted for arbitrary correlation within state-year cells and reported in parentheses. Elasticity estimates, evaluated at the sample mean, are presented in brackets. Significance is denoted as follows: *** $p \leq 0.01$, ** $0.01 < p \leq 0.05$, * $0.05 < p \leq 0.10$.
[2] State covariates include total number of substance abuse treatment admissions in the state, state-level personal income per capita, state unemployment rate, state population, and state substance abuse treatment block grant.
[3] For computing convenience, analyses are performed on a 35 percent random sample. The difference in sample size between specifications 1 and 2 mostly represents missing information for insurance status.

Table 6
Heroin Treatment Admission [1]
Linear Probability Models

Sample	All			Self Referrals	Criminal Justice Referrals
Model	1	2	3	4	5
Dependent Variable	Heroin Admission	Heroin Admission	Primary Heroin Admission	Heroin Admission	Heroin Admission
Heroin Price	-0.00051* (0.0003) [ε = -0.002]	0.00017*** (0.0001) [ε = 0.001]	-0.00004 (0.0001)	-0.00006 (0.0001)	0.00037*** (0.00004) [ε = 0.004]
Age	0.0164*** (0.0012)	0.0160*** (0.0014)	0.0088*** (0.0010)	0.0079*** (0.0021)	0.0148*** (0.0013)
Age-squared	-0.0002*** (0.00002)	-0.0002*** (0.00002)	-0.0001*** (0.00001)	-0.0001*** (0.00003)	-0.0002*** (0.00002)
Male	-0.0274*** (0.0029)	-0.0283*** (0.0032)	-0.0260*** (0.0033)	-0.0233*** (0.0037)	-0.0274*** (0.0028)
Black	0.0164** (0.0073)	0.0282*** (0.0097)	0.0536*** (0.0083)	0.0047 (0.0119)	0.0552*** (0.0102)
Other Race	0.0482*** (0.0066)	0.0307*** (0.0096)	0.0424*** (0.0117)	0.0647*** (0.0097)	-0.0052*** (0.0053)
Hispanic	0.1605*** (0.0086)	0.1071*** (0.0092)	0.0922*** (0.0102)	0.1539*** (0.0096)	0.0523*** (0.0071)
High School	-0.0061*** (0.0017)	-0.0042** (0.0021)	-0.0009 (0.0017)	-0.0175*** (0.0025)	-0.0131*** (0.0025)
College	-0.0608*** (0.0042)	-0.0583*** (0.0053)	-0.0458*** (0.0043)	-0.0883*** (0.0064)	-0.0283*** (0.0038)
Full-time Employed	–	-0.1065*** (0.0056)	-0.0755*** (0.0054)	-0.0452*** (0.0066)	-0.0845*** (0.0064)
Part-time Employed	–	-0.0834*** (0.0049)	-0.0609*** (0.0052)	-0.0406*** (0.0061)	-0.0700*** (0.0052)
Private Insurance	–	-0.0764*** (0.0073)	-0.0669*** (0.0088)	-0.1403*** (0.0139)	-0.0452*** (0.0041)
Public Insurance	–	0.0286*** (0.0061)	0.0285*** (0.0053)	0.0528*** (0.0061)	-0.0120*** (0.0036)
Drug-related Arrests	–	0.0034*** (0.0004)	0.0027*** (0.0003)	0.0048*** (0.0004)	0.0020*** (0.0003)
State Covariates [2]	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
State Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.156	0.193	0.199	0.242	0.122
Observations [3]	5,453,802	1,905,139	876,190	694,511	649,237

[1] Heroin Admission represents a dichotomous indicator of whether cocaine is mentioned as a first, second, or third substance of abuse related to the treatment admission. Primary Heroin Admission refers to a dichotomous indicator for whether cocaine is the primary and only substance of abuse. Estimates from linear probability models are presented. Standard errors are adjusted for arbitrary correlation within state-year cells and reported in parentheses. Elasticity estimates, evaluated at the sample mean, are presented in brackets (when the underlying marginal effect is statistically significant). Significance is denoted as follows: *** $p \leq 0.01$, ** $0.01 < p \leq 0.05$, * $0.05 < p \leq 0.10$.
[2] State covariates include total number of substance abuse treatment admissions in the state, state-level personal income per capita, state unemployment rate, state population, and state substance abuse treatment block grant.
[3] For computing convenience, analyses are performed on a 35 percent random sample. The difference in sample size between specifications 1 and 2 mostly represents missing information for insurance status.