Finlay is the corresponding author. Neither author has a financial interest or conflict of interest related to the findings reported in this paper. Data and codes may be obtained from the corresponding author.

Identifying Demand Responses to Illegal Drug Supply Interdictions

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Abstract

Successful supply-side interdictions into illegal drug markets are predicated on the responsiveness of drug prices to enforcement and the price elasticity of demand for addictive drugs. We present causal estimates that targeted interventions aimed at methamphetamine input markets ("precursor control") can temporarily increase retail street prices, but methamphetamine consumption is weakly responsive to higher drug prices. After the supply interventions, purity-adjusted prices increased then quickly returned to pre-treatment levels within 6-12 months, demonstrating the short-term effects of precursor control. The price elasticity of methamphetamine demand is -0.13 to -0.21 for self-admitted drug treatment admissions and between -0.24 to -0.28 for hospital inpatient admissions. We find some evidence for a positive cross-price effect for cocaine, but we do not find robust evidence that increases in methamphetamine prices increased heroin, alcohol, or marijuana drug use. This study can inform policy discussions regarding other synthesized drugs, including illicit use of pharmaceuticals.

Keywords: illegal drugs, addiction, demand, substitution, War on Drugs, methamphetamine
JEL codes: I12, I18, K42

1 Introduction

Policymakers trade off the social costs of addiction with the costs of enforcement when designing optimal drug policy. Costs for the enforcement of drug laws are as much as $40 billion annually in the US (**?**). The US incarceration rate per 100,000 residents grew from 100 in 1980 to 492 in 2011 as the share of prisoners convicted of drug offenses increased from 22% to 48% (**??**). Although violence associated with drug trafficking is a major urban problem, the marginal efficacy of enforcement-oriented interventions is uncertain given evidence of diminishing returns to incarceration (**?**). Policies that attempt to reduce demand by increasing drug prices may also be ineffective if drug addicts have inelastic demand with respect to prices.

There are few causal estimates of illegal drug demand because of the difficulty of obtaining exogenous variation in prices and reliable indicators of use. The simultaneity of supply and demand for each drug confounds estimates of demand elasticities as a causal measure of demand response to price changes. For example, suppose that the government chooses an enforcement policy for reducing illegal drug consumption, then increases the number of police tasked with arresting drug traffickers and users. This strategy will both increase production costs for providers and increase the risk of punishment for users. The measured demand response will reflect both price changes caused by enforcement and non-pecuniary costs incurred by users.

In this paper, we estimate the causal demand response of drug users to price changes by exploiting several federal and state supply shocks to methamphetamine (meth) markets. Meth is synthesized from either ephedrine or pseudoephedrine ("chemical precursors"). Throughout the 1990s and 2000s, federal and state legislators occasionally curtailed the domestic production of meth through the regulation of wholesale and retail distribution of chemical precursors. These legislations temporarily disrupted meth markets by creating brief shortages of key inputs. Real prices of a pure gram of meth rose considerably following each regulation, thereby providing a quasi-experiment to identify the short-run price elasticity of demand for meth. We use two measures of meth-related public health outcomes as proxies for meth, or "proxy demand": monthly data on inpatient hospitalizations and self-admitted substance abuse treatment admissions by state.[1] We use International Classification of Disease (9th edition) codes to identify meth mentions in hospital

[1] See **?** for a similar use of proxies that measure the extent of drug users rather than the intensity of drug consumption.

inpatient records.[2] Our proxy based on treatment admissions classified use depending on whether meth was mentioned in the last substance episode before entering treatment. We measure retail drug prices from undercover law enforcement purchases and control for other relevant factors for US states from January 1994 to December 2010. Using indicators for the meth supply interventions as instruments, we estimate the causal effect of meth prices on hospitalizations and treatment admissions for meth and various substitute substances.

We find that the demand curve for meth is downward-sloping and inelastic for the complier population of consumers. This suggests that meth dependency can only be somewhat curtailed through higher retail prices. We find evidence for substitution effects for crack/cocaine (hereafter: cocaine), but do not find robust evidence for positive cross-price elasticities for alcohol, marijuana, or heroin.

? estimate the causal effect of a 1995 federal intervention into ephedrine markets using California county-level panel data. They find that while the interdiction raised meth prices and reduced meth consumption, there was no effect on crime itself. The study is one of the few well-identified studies to estimate the causal effect of drugs on crime. **?** use state panel data from 1995 to 2000 and estimate the causal effect of meth use on foster care admissions using the 1995 and 1997 federal ephedrine and pseudoephedrine interdictions, respectively. While both studies utilize the effect that 1990s precursor control policies had on meth-related outcomes, neither explicitly estimates the price elasticity demand for meth. Furthermore, neither estimates cross-price effects. **?** evaluate the impact that over-the-counter retail pseudoephedrine regulations during the 2000s had on meth consumption and meth production, but do not estimate own and cross-price elasticities.

Our study makes several contributions. We present compelling evidence that the demand for meth is negatively sloped but inelastic. We use an instrumental variables strategy for estimation to provide more convincing evidence that the negative correlation between price and quantity is causal and not spurious. We also show that regulations of meth precursors, ephedrine and pseudoephedrine, were only temporarily effective at disrupting input and output markets. We conclude that the partial regulation of illicit drug inputs is not an effective long-run strategy. So long as producers can substitute away from regulated inputs, supply interdictions are at best only temporarily effective at raising prices and reducing consumption. Our study is also the first to use

[2] See Data Section for the list of ICD-9-CM codes used to identify meth incidence in hospitalization data.

a state panel of meth hospitalizations and treatment admissions to estimate meth proxy demand elasticities, federal and state chemical precursor interventions to identify meth proxy demand elasticities, and supply-side shocks to estimate cross-price drug proxy demand elasticities. We estimate a price elasticity of meth demand, based on proxies, of -0.13 to -0.21 for self-admitted meth treatment demand and between -0.24 and -0.28 for meth inpatient hospitalizations. We find minimal evidence that these price shocks shifted demand to other substances, which suggests that the shocks were capable of decreasing meth addiction to reduced levels without shifting that addiction to other substance abuse observable in our dataset. Under zero marginal costs of enforcement and with a short-run own-price elasticity of -0.20, we conclude that precursor control is socially optimal if the negative social externalities from meth are five times the private value to users. In reality, enforcement costs are nonzero and legitimate medical users are inconvenienced by precursor restrictions, so precursor control is unlikely to be cost effective.

Next, we provide background on meth use and production, how synthesis allows precursor control, and an economic approach to optimal drug policy. We then describe the empirical model and the data, discuss our results, and conclude.

2 Background

Methamphetamine

The large economic costs of substance abuse include the impact of addiction on quality of life, labor productivity, public resources, crime, and the families of users.[3] Meth, the focus of this study, is the second most widely used class of drugs worldwide after cannabis (**?**). Damages originating from its domestic production and use, such as child maltreatment, foster care admissions, environmental damage, and hospitalization, greatly contribute to meth's high social cost—estimated at \$23.4 billion in 2005 (**?**).

Meth is relevant for evaluating drug policy because its social costs are large and its production process may allow cost-effective supply interdictions. Unlike many other illegal drugs, meth is synthesized from chemical precursors produced in concentrated global input markets. Restricting precursor supplies can decrease quantity and increase price without potentially increasing im-

[3]See **?**; **?**; and **?** for a review of the social costs of substance abuse and risky behaviors.

prisonment. Compared to public awareness campaigns targeted at meth demand (?), precursor controls have been more successful at reducing consumption (???). But precursor controls may have only temporary effectiveness because of large potential profits in underground meth markets and incomplete regulation of precursor supply chains.

Meth poses challenges to policymakers because of its high social costs as well as the role addiction plays in sensitivity to prices. A large share of meth's total costs have been attributed to the external impact of meth use on nonusers from harm to children, crime, and pollution (?). Only a few studies have estimated the causal effect of meth use on public health outcomes. **?** find no evidence that meth causes crime, whereas **?** estimate a positive elasticity of foster care admissions with respect to meth use from increased child neglect and abuse.[4]

Precursor control

Policy efforts to increase drug prices through supply-side interventions have had ambiguous results. An early study of cocaine control by **?** found that domestic enforcement and source country interdictions were less cost-effective than treatment for cocaine dependency. Some studies fail to find evidence that supply-side enforcement raises illegal drug prices (??). Given the high social costs of incarceration, enforcement strategies may not be cost effective (?).

There are some examples of potentially effective supply-side interdictions. Policies aimed at disrupting meth's input markets appear able to reduce meth availability and raise meth prices—at least temporarily. Meth is synthesized from a reduction of ephedrine or pseudoephedrine, the active ingredients in commonly used cold medicines, and therefore the illegal meth product market depends critically on access to legal chemical inputs. While cold medications can be purchased at retail pharmacies, large quantities of bulk precursors can only be obtained in wholesale outlets. These chemicals are imports subject to chemical trafficking regulations.

These precursors are distributed and packaged in different forms which creates challenges for regulators and opportunities for meth producers. In 1988, Congress passed the Chemical Diversion and Trafficking Act that gave the DEA the authority to control the wholesale distribution of precursors used to produce illegal drugs, such as meth. The statute required bulk distributors of

[4] These relationships may be explained by differences in brain chemistry between meth users and non-users. Meth dependency affects user brain chemistry with evidence of long-term increases in psychosis, paranoia, and aggression (?).

ephedrine and pseudoephedrine to notify drug enforcement authorities of imports and exports and keep records of purchasers (**?**). All tablet forms of ephedrine and pseudoephedrine medical products, however, were exempt—a legal loophole that drug trafficking organizations quickly exploited.

An unintended consequence of precursor regulations was substitution towards unregulated precursors. Pseudoephedrine is a perfect substitute for ephedrine, but was not historically used by domestic meth labs. In 1994, pseudoephedrine was the primary precursor in 2% of all meth lab seizures, while ephedrine accounted for 79% (**?**). Congress passed the Domestic Chemical Diversion Control Act to reduce the flow of ephedrine medical products to the underground market (**??**). The new legislation, which took effect in August 1995, ignored pseudoephedrine tablets and traffickers quickly substituted toward pseudoephedrine as a precursor. By 1996, pseudoephedrine was the primary precursor in almost half of meth lab seizures (**?**).[5] Congress responded and passed the Comprehensive Methamphetamine Control Act of 1996 to close the loophole on pseudoephedrine tablets (**?**). It came into effect between October and December 1997.

Suppliers ability to both substitute between precursors, as well as across precursor supply chains, undermined the longterm efficacy of the major mid-1990s wholesale regulations. DEA intelligence suggested that large-scale meth production relocated into Mexico following the Comprehensive Methamphetamine Control Act. By the early 2000s, the purity of meth had been rising and returning to its historically high levels (Figure **??**). Furthermore, small-scale production remained a problem in the US due to the lax controls on pharmacy-level distribution of pseudo-based cold medications. This prompted a rapid wave of state-level regulations of over-the-counter pseudoephedrine-based cold medications (**?**). These regulations varied along three main dimensions: required identification at point of purchase, maximum purchase limits (usually measured as 9 grams of pseudo per month per customer), and requirements that pseudo be placed behind-the-counter of the pharmacy (as opposed to over-the-counter). The federal Combat Methamphetamine Epidemic Act—passed in March 2006 and effective in October 2006—bound all remaining states to these pharmacy restrictions.

While the Combat Methamphetamine Epidemic Act was a major federal policy, states continued to experiment with precursor control policies. Two types of proposals have emerged after

[5] Between 1996 and 1997, pseudoephedrine imports grew 27% while sales of all cold medications grew only 4% (**?**).

CMEA: requiring a doctor's prescription for purchases and statewide computerized database tracking consumer purchases of pseudoephedrine. Oregon (2006) and Mississippi (2010) passed laws that scheduled pseudoephedrine-based cold medications, and thereby force consumers to obtain a doctor's prescription before they can purchase these products. Other states have chosen to increase the monitoring of transactions as an alternative to further precursor control. Electronic tracking uses the National Precursor Log Exchange (NPLEX) software to provide pharmacies and law enforcement with a common database on all state-wide cold medications and is viewed as a less intrusive reform than requiring a prescription. As an incentive, the pharmaceutical industry provides the software at no cost to any state that passes legislation requiring electronic tracking. Approximately two dozen states use NPLEX with more states considering it every year.

In the short-run, precursor controls have been the most successful supply-side interdictions in the history of US drug enforcement (**?**), but the long-run effects of these wholesale regulations have been more muted. Meth producers adapted by substituting to over-the-counter cold medications containing pseudoephedrine for their precursor supply and relocating operations out of the US. Evidence of the temporary success can be found in time series data of purity-adjusted meth prices. We construct a monthly price series from January 1995 to December 2010 for a pure gram of meth, heroin, and cocaine using the DEA's System to Retrieve Information from Drug Evidence (STRIDE) database.[6,7] We use an empirical method to identify the windows during which each intervention was effective by first regressing real expected meth prices onto a cubic time trend. We then add a single-month fixed effect for each month after the intervention began—retaining only those that are statistically significant. We repeat these steps until the last contiguous, post-intervention month dummy variable is statistically insignificant. The Domestic Chemical Diversion Control Act became effective in August 1995, and our method identifies deviations in price trends from September 1995 until February 1996. The Comprehensive Methamphetamine Control Act became effective between October and December 1997, and our model identifies deviations in price trends from April 1998 to March 1999.[8] The state and federal laws from 2000 to

[6]See Appendix **??** for a more detailed explanation of the construction of the drug price series used in the paper.

[7]There is a debate about the ability of researchers to recover the distribution of market prices from STRIDE because its sampling is determined by law enforcement actions. See **?** for the critical argument and **?** for a rebuttal.

[8]Our empirical method for dating the interventions in this paper is similar to previous studies. **?** use a four-month window for the 1995 intervention, but they limit their attention to California where the meth market is the most sophisticated and producers are arguably more adaptable. **??** use six months for the 1995 intervention (August 1995–January 1996).

2010 were coded based on their resemblance to the federal Combat Methamphetamine Epidemic Act (CMEA). CMEA had several distinctive features: all pseudoephedrine-based cold medications required identification and a paper log tracking purchases; all pharmacies were required to move pseudoephedrine-based cold medications "behind-the-counter"; and no more than 3.6 grams of pseudoephedrine per day (9 grams per month) could be sold to any single consumer. We code pre-CMEA states as having CMEA-equivalent requirements if they meet or surpass these limits.

Figure **??** shows the median monthly retail expected price of meth, heroin, and cocaine relative to their respective median values in January 1994. Beer prices are also included but come from a separate data source of retail prices that we describe below. We denote the effective window of the three federal interdictions with gray boxes. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.[9][10] The 1995 shock caused meth prices to nearly quadruple over its 1994 level briefly. Prices returned to pre-interdiction levels after six months. The 1997 interdiction was comparatively smaller in magnitude, but caused meth prices to double over their pre-interdiction levels for twelve months. The 2006 interdiction had the smallest effect recorded of the three major federal regulations.[11]

Increases in the real price of a pure gram of meth are caused by increases in the cost of purchases and substantial declines in purity. These large but temporary disruptions in meth markets are key to our identification strategy. Note that there is no comparable change in heroin, cocaine, or beer prices relative to pre-interdiction levels during either intervention suggesting that the price disruptions are the result of factors unique to meth markets and are not confounded by broad enforcement changes.

[9] Not shown are the dozens of state-level interventions from 2000 to 2006, or NPLEX or Rx in particular. (**?**).

[10] All changes went into effect on March 9, 2006, (date the legislation was signed) unless a later effective date was specifically stated. All logbook provisions, sales limits, and product placement regulations went into effect on September 30, 2006.

[11] Since 2000, there have been a variety of state-level precursor controls, ranging from quantity restrictions to electronic tracking of purchases to doctor prescription requirements. Since producers can obtain inputs from neighboring states, the price effects of these interventions are smaller and evidence suggests the demand responses are also smaller (**??**).

Optimal drug policy

Public policies that increase the price of addictive goods are welfare enhancing only if the following two hypotheses are correct. First, supply-side interventions can theoretically reduce demand through higher prices so long as demand is downward sloping. **?** showed that budget constraints are sufficient to deter consumption when prices rise. Later work by **?** extended the model of rational addiction—highlighting the importance of parameters like the price elasticity of demand in optimal drug policy. The second hypothesis concerns the internal and external harm from consumption of addictive goods. Addiction is sub-optimal if users impose externalities on others or if users fail to optimize utility over present and future consumption due to time-inconsistent preferences (**?**).

In their economic approach to drug policy, **?** contrast the social welfare under a free market for drugs with a regime where drug quantities are reduced through enforcement and punishment. They show that the optimal level of enforcement depends on whether demand is inelastic, the size of the negative externalities from drug consumption, and the costs of enforcement. If the social planner wishes to choose a level of enforcement, E, that maximizes the net benefits of consumption minus the sum of production and enforcement costs, then the following first-order condition must hold in equilibrium:

$$C_1 + C_2(Q + E\frac{dQ}{dE}) + C_3(\theta\frac{dQ}{dE} + Q\frac{d\theta}{dE}) = V_q\frac{dQ}{dE} - MR\frac{dQ}{dE}, \tag{1}$$

where Q is the quantity of drugs consumed, θ is the odds-ratio expression of the probability of arrest, V_q is the marginal social willingness-to-pay for illegal drug consumption, and MR is the marginal revenue for drug suppliers. The marginal cost of enforcement contains both a public good component, C_1, that is invariant to the quantity of drugs, and a private component, C_2, that varies with quantity. The final component of the marginal cost of enforcement is C_3, which measures the costs of punishing arrested users. The right-hand side of Equation **??** measures the marginal benefit of reduced consumption.

If we assume that the marginal costs of enforcement are zero, we can rearrange Equation **??** so that the role of the price elasticity of meth demand is more transparent:

$$\frac{V_q}{P} = 1 + \frac{1}{\epsilon_d}, \tag{2}$$

where P is the consumer drug price and ϵ_d is the price elasticity of demand for the drug. Price equals the private willingness-to-pay in competitive markets, so the left-hand side of Equation **??** equals the ratio of marginal social to private value of illegal drug consumption. If demand is inelastic, then both the right-hand side and left-hand side of Equation **??** must be negative in order for non-zero levels of drug enforcement to be optimal. This requires negative externalities in consumption, $V_q < 0$, given that price is non-negative.

If demand is inelastic and negative externalities are relatively small, then unrestricted meth consumption is socially optimal. This is because production and distribution costs are rising as output falls at a loss in social utility from reduced consumption. If meth demand is inelastic, then government intervention is justified if and only if the social value of meth consumption is "very negative." Thus even in a world where the marginal costs of enforcement are essentially zero, inelastic demand implies that enforcement is optimal only when there are substantial negative externalities, and even then, quantity restrictions will absorb a considerable amount of resources. If marginal costs are positive, then marginal enforcement costs increase as demand becomes less elastic because of the slower declines in consumption. And since expenditures on apprehension and punishment depend on output, a slower fall in output with inelastic demand will cause enforcement expenditures to grow more rapidly.

When demand is elastic, then whether it is socially optimal to reduce output depends on whether consumption of the good has positive marginal social value. If the elasticity is as high as -1.5, then Equation **??** shows it may still be socially optimal to do nothing if the ratio of marginal social to marginal private value exceeds one-third. **?** write, "it takes very low social values of consumption, or very high demand elasticities, to justify intervention, even with negligible enforcement costs" (p. 48).

Estimates of price elasticities of drug demand

An estimate of the price elasticity of meth demand could enable policymakers to evaluate the cost effectiveness of different interventions. Most economic studies suggest that addictive substances are consumed on the inelastic portion of demand. Price elasticities of demand for tobacco are in the range of -0.3 to -0.5 (**??**). The median price elasticity of demand for alcohol is -0.55 (**?**) with findings of less elastic demand for beer and more elastic but still inelastic demand for wine and spirits (**??**).

Evidence on cross-price elasticities for addictive substance demand is much less developed. Most studies examine within-category substitution. For example, **?** find a unit-elastic cross-price elasticity of snuff use with respect to cigarette prices, whereas **?** estimate a negative cross-price elasticity for cigarettes with respect to alcohol price, which suggests they are complements.

There are challenges to estimate price elasticities for illicit substances. Observing measures of consumption is inherently difficult, so researchers generally rely on proxies that reflect drug user interactions with hospitals, treatment centers, and the criminal justice system. For example, **?** uses emergency department visits as a demand proxy and estimates very inelastic demand for cocaine (-0.27) and heroin (-0.10). Using other hospitalization data, **?** finds that demand is less inelastic for heroin (-0.84) and elastic for cocaine (-1.30). **?** estimate -0.82 to -1.03 for heroin elasticities of demand, and -0.28 to -0.44 for cocaine. Evidence from historical opium markets demonstrate that long-run demand can be elastic even if short-run demand is quite inelastic (**??**). **?** estimate elastic demand for heroin (-1.23) among 500 self-reported Norwegian heroin users. **?** estimate a -0.30 own-price elasticity of demand for marijuana. Our estimates in this paper fall in the most inelastic parts of these ranges.

Insofar as the unobserved "light" consumers of meth are like addicts that appear in our data, then the elasticities of meth demand, based on our meth proxies, may be generalizable. Some writers suggest that this may be true for meth. **?** note that the distribution of consumption for addictive goods is ordinarily bimodal with most consumers consuming zero of the good, and others consuming in dangerously high quantities. **?** note that "few people consume small quantities of crystal meth or crack cocaine year after year; people tend to quickly converge to either a steady state with high consumption (addiction) or one with zero consumption (abstinence)."

3 Estimation, identification, and data

We are interested in the causal demand response for meth m, alcohol a, marijuana mj, cocaine c, and heroin h (with drugs indexed by i). Consider log-log demand equations of the form:

$$\ln(Q_{st}^{m}) = \beta_{\text{OLS}}^{m,m} \ln(P_{s,t-1}^{m}) + \gamma^{m} X_{st} + \varepsilon_{st}^{m} \tag{3}$$

$$\ln(Q_{st}^{i}) = \beta_{\text{OLS}}^{i,m} \ln(P_{s,t-3}^{m}) + \beta^{i,i} \ln(P_{s,t-1}^{i}) + \gamma^{i} X_{st} + \varepsilon_{st}^{i} \qquad \forall i \in \{a, mj, c, h\}, \tag{4}$$

where Q is a drug demand proxy (either self-referred admissions or hospitalizations related to the drug of interest), $P_{s,t-j}^{m}$ is the j-month lagged retail price of a pure gram of meth (m), and ε is the error term. We use a 3-month lagged meth price ($j = 3$) for our cross-price elasticity equation to accommodate delayed substitution across substance category and a 1-month lagged meth price ($j = 1$) for the own-price elasticity equation. The vector X includes state fixed effects, month-of-year effects, various time trends, the log of the state population aged 15–49 years, and the state unemployment rate. The unit of observation is state s in month t, and all regressions are weighted by the population aged 15–49 years. The parameters of interest are $\beta^{m,m}$, the own-price elasticity of meth proxy demand, and the $\beta^{i,m}$s, the cross-price proxy demand elasticities for the other drugs with respect to meth prices.

Price and quantity in Equations **??** and **??** are observed in market equilibrium. The simultaneity of supply and demand for each drug confounds the interpretation of the $\beta_{\text{OLS}}^{\cdot,m}$s as causal measures of the demand responses to price changes. For example, if the government chooses a prohibition and enforcement policy for reducing illegal drug consumption, then the number of police tasked with arresting drug traffickers and users will increase. This strategy, potentially unobservable to the researcher, will both increase production costs for providers and increase the risk of punishment for users. The equilibrium prices and quantities reflect both of these responses, so $\beta_{\text{OLS}}^{\cdot,m}$ may be biased by the omission of unobserved law enforcement variables.

To identify the causal demand response to drug price changes, we use an instrumental variables strategy and estimate a two-stage least squares (2SLS) model. Our main specification of the instrumental variable is an indicator variable equal to one for the month durations that the 1995, 1997, and 2006 federal interventions had significant disruptions on meth markets and zero for all other months (as described above). We also use dummy variables to denote states that have the NPLEX and prescription-only interventions. The second-stage demand models become:

$$\ln(Q^m_{st}) = \beta^{m,m}_{\text{IV}} \ln(\widehat{P^m_{s,t-1}}) + \tilde{\gamma}^m X_{st} + \tilde{\varepsilon}^m_{st} \tag{5}$$

$$\ln(Q^i_{st}) = \beta^{i,m}_{\text{IV}} \ln(\widehat{P^m_{s,t-3}}) + \tilde{\beta}^{i,i} \ln(P^i_{s,t-1}) + \tilde{\gamma}^i X_{st} + \tilde{\varepsilon}^i_{st} \qquad \forall i \in \{a, mj, c, h\}, \tag{6}$$

where $\ln(\widehat{P^m_{s,t-j}})$ is the fitted log meth price from our first stage model. To identify $\beta^{\cdot,m}_{\text{IV}}$, the instrument Z_t must be correlated with meth prices, which we establish in Figure **??**. Identification also requires that the instrument only affect drug demand through its effect on meth prices. Although we know of no contemporaneous increases in law enforcement effort during the intervention periods, we focus on self-admitted treatment admissions and hospitalizations with meth mentions to isolate the demand response that is most likely to be independent of police effort.[12] Since we do not observe individual consumption, but rather meth mentions in hospitals and treatment facilities, we interpret $\beta^{m,m}_{\text{IV}}$ as the own-price elasticity of meth proxy demand. Graphical analysis of the price series data, as well as earlier literature, is suggestive of a temporarily disruptive precursor intervention.

To estimate Equations **??**–**??**, we combine state-month data from a variety of sources. We choose a sample period of January 1994 to December 2010 for all datasets. This starts eight months before the first intervention and ends nine months after the second intervention. We construct an estimated price series for a pure gram of meth, heroin and cocaine using the DEA's System to Retrieve Information from Drug Evidence (STRIDE) dataset. All prices are adjusted to 2013 dollars using the All Urban Consumer Price Index series. Drug price observations do not occur in every state-month cell. To impute price observations for missing cells, we take observed price averages from higher level geographic areas, moving from states, to census divisions, to census regions, and finally to national price series. This imputation should reflect the price users must pay in a particular state. We show a comparison of both sets of price series in Table **??**. Each pair has a similar mean but the sets with imputed prices have smaller variances. For alcohol prices, we aggregate from retail prices recorded by ACCRA for beer, wine, and distilled spirits. Liquor prices

[12] The local average treatment effect interpretation of the IV parameter is a consideration if price responses to interventions are systematically different in intervention periods. We have no reason to believe heterogeneity in demand responses to price exists, but the first-stage monotonicity requirement is likely to be satisfied in any case.

are based on specific product sizes (e.g., six pack, etc.). To measure the availability of marijuana, we include a medical marijuana legislation indicator in the marijuana demand equation.[13]

We use two proxies for drug demand: self-admitted drug treatment admissions and hospital inpatient admissions. Drug treatment admissions data come from the Department of Substance Abuse and Mental Health Administration's Treatment Episode Data Set (TEDS). TEDS records the universe of all federally funded treatment inpatient or outpatient facilities. Patients admitted are interviewed to determine the routes of admission, as well as which substances were used at their most recent treatment episode. We use the number of treatment admissions by substance abuse category as proxies for the following substances: meth, alcohol, cocaine, heroin, and marijuana. We report the total admissions aggregated over all routes of admissions as well as the number of self-referred admissions for each substance in our descriptive statistics, but only use self-admissions in our regression models. Only Oregon and Arizona distinguish between meth and other amphetamine stimulants; the rest count all amphetamine stimulants as meth. But, 95% of all combined methamphetamine/amphetamine admissions are methamphetamine.[14]

Inpatient hospitalizations come from the Healthcare Cost Utilization Projects (HCUP) Nationwide Inpatient Sample (NIS). The NIS is a database of hospital inpatient stays and is the largest all-payer inpatient care database that is publicly available in the US. The NIS provides patient-level clinical and resource use information on between five million to seven million inpatient stays from approximately 1,000 hospitals each year, and approximates a 20-percent sample of US community hospitals.[15] Inpatient stay records in the NIS include clinical ICD-9-CM diagnoses for each patient and these were used to identify all instances of amphetamine mentions.[16]

? suggests that proxies in illegal-drug research are preferred because of the inherent difficulty in observing underground markets and the underreporting of illegal behavior in surveys of individual behavior. We also need monthly data to properly time the meth precursor interventions

[13]Most marijuana observations in STRIDE are from seizures that have no associated price data. Marijuana purity also is not available, making it impossible to generate price or purity series using these data.

[14]See `http://wwwdasis.samhsa.gov/webt/information.htm` (accessed on 14 February 2015).

[15]US community hospitals are defined by the American Health Association to be all non-federal, short-term, general, and other specialty hospitals, excluding hospital units of institutions, such as obstetrics-gynecology, ear-nose-throat, short-term rehabilitation, orthopedic and pediatric institutions. Also included are public hospitals and academic medical centers, but excluded are all short-term rehabilitation hospitals, long-term hospitals, psychiatric hospitals, and alcoholism/chemical dependency treatment facilities.

[16]See Appendix Table 1 for the list of ICD-9-CM codes used to identify meth and other substances incidence in hospitalization data.

which favors the use of administrative records on inpatient hospitalizations and admissions to drug treatment facilities since each contains high frequency information about indicators correlated with meth use and contain enough observations that can be aggregated to the state-month level. Hospitalizations and treatment admissions primarily proxy for critically high levels of meth abuse, but given the social costs of meth use are primarily attributable to these individuals, it is likely that this is the most policy-relevant group on which to focus. Since meth consumption may be bimodal at zero and heavy consumption, treatment and hospitalizations are likely highly associated with underlying behavior itself.

While each data source is likely correlated with drug use, they differ in important ways. One key difference between the two data sources is the number of co-morbid substances consumed at the time of admission. TEDS limits the number of reported substances consumed in the last substance abuse "episode" to three, whereas NIS allows up to 15 separate diagnoses per inpatient record. The TEDS records will be biased towards finding positive cross-price proxy demand elasticities if precursor control effectively reduces meth consumption and meth users consume more than three substances at the last episode.[17] We use inpatient data in addition to treatment data when estimating meth-related elasticities.

The population of those aged 15–49 years in each state in 1,000s comes from SEER (**?**). State-level unemployment rates were obtained from the Current Population Survey. We also include state cigarette taxes measured as real dollars per cigarette pack (**?**).

4 Results

We first present figures that show aggregate meth mentions from the NIS and TEDS. Figure **??** displays self-admitted treatment mentions of meth and inpatient hospitalizations for meth over the sample period. The NIS data were collected in a limited set of states in the sample period, so we present the TEDS results using both the full TEDS sample and the smaller NIS sample. We

[17] Consider the following simple example for illustrative purposes. If a meth user consumed (1) meth, (2) alcohol, (3) cocaine and (4) marijuana at his last episode, then only substances one—three would be listed. If this person discontinued using meth following an effective intervention, but entered treatment for one of the other substances on this list, then we would estimate negative elasticities of meth and a positive cross-price elasticity of marijuana with respect to meth price due to marijuana shifting into positions one through three. Similarly, if the person did not enter treatment at all because of falling meth purity and rising meth price, but continued to consume alcohol and cocaine, we would estimate negative cross-price proxy demand elasticities for alcohol and cocaine despite no change in consumption.

deflate the data using the starting value from January 1994 so that each data series can be placed on the same y-axis and compared over time. Self-admitted treatment admissions grew steadily to approximately 60% over its January 1994 level when the first intervention occurred. Immediately following the 1995 interdiction, self-admitted treatment admissions fell to a level approximately 10% higher than the January 1994 levels. Meth treatment admissions steadily grew after the first intervention wore off until early 1998 when the second pseudoephedrine regulation was effected. At this point in the series, meth mentions again fell to only 10% over the 1994 levels followed by a temporary plateau. But just like before, prices returned to pre-treatment levels and meth treatment admissions reverted to its earlier upward trend. This growth continued for several years until several states passed over-the-counter laws restricting use. By 2005, meth treatment admissions were more than twice their 1994 levels. Steep declines in admissions occurred prior to CMEA's enactment date as dozens of states passed their own over-the-counter regulations (**?**). Admissions stabilized in late 2007, shortly after Mexico's ban on pseudoephedrine imports, but have yet to reach the height of the pre-CMEA period.[18]

The time series for meth hospitalizations shows a similar response to the price shocks during the 1995 supply interdiction, although hospitalizations grew more rapidly relative and fell more steeply. Meth hospitalizations were considerably more responsive to the pseudoephedrine interdictions in 1997 than treatment admissions. Self-admitted treatment admissions data cover more states than the inpatient hospitalization data, so some of the difference in responsiveness might be due to sample selection. We examine this by comparing the responsiveness of self-admitted treatment admissions with inpatient hospitalizations using the same set of states, but we still find that hospitalizations are more responsive to the first and second interdictions. After the efficacy of the 1997 pseudoephedrine regulation tapered off, meth hospitalizations grew steadily through the early 2000s. During the 2006 CMEA interdiction, hospitalizations and treatment admissions responded to CMEA at different times—treatment admissions fell at or just before the CMEA enactment date, whereas hospitalizations fell several months later when CMEA became effective. Whereas the two series closely track one another, hospitalizations appear more responsive to the effective dates of the federal regulations.

It is possible that unobserved consumption shocks coincidental to the numerous interdictions

[18]See `http://www.justice.gov/archive/ndic/pubs38/38661/meth.htm` (accessed on 7 January 2015).

occurred and therefore have biased our estimation strategy. To check, we overlaid TEDS admissions for four other drugs with meth. Figure **??** does not reveal any clear change in the time path of alcohol, heroin, cocaine, or marijuana patterns in the TEDS series during any of the interdiction episodes we examined. Figure **??** shows the inpatient hospitalizations series for the same four substances overlaid with meth, and it reveals no unusual patterns common to substance abuse or treatment during the interdiction episodes.

Next we present regression estimates of price elasticities of meth mentions for treatment admissions and hospitalization inpatient records. All models use the log of the treatment admissions as dependent variables and log of meth prices as the independent variable. The regressions all have a log-log form, so the coefficients are approximately equal to elasticities. Our meth variable includes all mentions of meth, but our other substance abuse variables exclude any cases where meth was mentioned so as to avoid double counting.[19] We use only self-admission cases because self-admit are those individuals who would be price responsive.[20]

Table **??** reveals a negative point estimate for the own-price proxy meth demand elasticity. The first stage results show that the real price of meth rose 47 log points during the two interventions, or 60 percent.[21] Since OLS and 2SLS both agree on the sign of the elasticity, we will report the 2SLS estimates since they are better identified. Models 2 and 8 for state and month fixed effects and a linear trend. Models 4 and 10 adds a state-specific linear trend, and Models 6 and 12 add state-specific quadratic trends. The models reveal similar elasticity measurements for treatment and hospitalization. The one-month price elasticity of meth proxy demand is -0.13 to -0.17 for treatment self-admissions and between -0.26 and -0.28 for inpatient hospitalizations.

We find that meth proxy demand is highly inelastic to retail meth prices unlike **?** who concluded meth demand was price elastic.[22] But compared to the estimated elasticities for other drugs, our estimates suggest that demand for meth is one of the more inelastic drug demands yet measured. The central tendency among all published elasticities for illegal drugs is negative one-

[19]TEDS admissions list their primary, secondary and tertiary substance used at the most recent episode, so it's possible for alcohol cases to occur with meth. As we do not want to bias downward estimates of cross-price proxy demand elasticities by including cases where meth appeared with other drugs, we focus on cases where meth is not mentioned at all, which we view as a conservative estimate.

[20]Criminal justice referrals, for instance, are usually instances where a judge assigned treatment to a defendant. The theory of demand would not suggest judges are making decisions in response to price fluctuations.

[21]The percentage change was calculated as $e^{0.47} \approx 1.60$.

[22]Since these are the first causal estimates of the own-price meth proxy demand elasticities, our findings may not directly comparable to **?**'s estimates of the same parameter.

half with a large standard deviation (**?**). Our one-month lagged own-price proxy demand elasticity of -0.26 to -0.28 using monthly NIS hospitalization is most comparable to **?**. He estimates own-price elasticity of annual cocaine hospitalizations of -0.27. Our one-month lagged own-price proxy demand elasticity of -0.13 to -0.17 using the TEDS treatment admissions data is also similar to his estimated own-price proxy demand elasticity among arrestees of -0.15 for cocaine and -0.10 for heroin.

Next we estimate various cross-price proxy demand elasticities with respect to meth prices. Figure **??** shows self-admitted treatment proxies for alcohol, heroin, cocaine and marijuana in addition to meth. There are no apparent breaks to any of the other series. We also graph hospital inpatients in Figure **??**, and find no apparent breaks in the series, as well.

We estimate cross-price proxy demand elasticities for all other substances in our datasets with and without the state-linear and quadratic trends, but as our results did not change, we present estimates using the fully specified model. We also estimate the cross-price elasticity of each substance with respect to meth prices using a 3-month lagged price since it is unlikely that immediate changes in meth prices would lead to additional substance abuse immediately. But we also estimated contemporaneous effects, and found essentially similar results as reported in Table **??**. As our 2SLS models have better identification, we will focus on those results.

We find no evidence that increases in meth prices caused changes in cross-substance abuse. Interestingly, some of the regressions using TEDS data reveal positive cross-price effects. But, if meth users consume more than three substances at their last episode, and rising meth prices indeed reduce meth consumption, then TEDS data is likely to yield spurious positive associations between meth price and the cross-substance as the declining meth mention is replaced by some other previously suppressed substance. For this reason, we believe the NIS hospitalizations data is more reliable for examining cross-price proxy demand elasticities since its top coding of 15 diagnoses is unlikely to be binding in these scenarios. But we fail to find any evidence for substitution using this measure either.

We now consider an alternative first-stage specification to exploit the separable disruption in prices. Table **??** presents that analysis using this separate first-stage specification. While the effect on the second stage estimates were negligible, this alternative specification reveals that each intervention has been less successful than the one before it. This may be explained by the fact that domestic production of meth has become a relatively small portion of total domestic consumption given the specialization of trade in other countries such as Mexico following the first 1995 intervention. This new specification allows us to report over identification tests. In some cases, the Hansen χ^2-statistic is statistically significant indicating a rejection of the overidentification restrictions. Given evidence that the earlier federal interventions were unanticipated, later interventions were possibly not exogenous (in the sense of being excludable from the demand models). Both the decreasing impact of subsequent interventions on price over time and the over-identification tests suggest that the long-term effect of these interventions are muted by suppliers anticipation of and response to the policies.

We also examine the effect of meth prices on other substance abuse categories using this alternative strategy (Table **??**). We do not find evidence from this analysis that rising meth prices caused changes in alcohol, heroin, or marijuana consumption. As both interventions were only temporarily effective at increasing meth prices, it is possible that long-run cross-price elasticities are different from what we present here. Further research is needed to understand the long-run cross-price elasticities of demand with respect to meth prices.

5 Conclusion

To evaluate the efficiency of alternative policies for addressing the public health costs of consumption of addictive drugs, researchers need causal estimates of the demand responses to those policies. Enforcement and prohibition strategies continue under the assumption that those efforts will increase prices sufficiently to reduce demand. If drug demand is price inelastic, **?** show that prohibition is only socially optimal if social externalities of drug use are much larger than the private benefits users get from drugs (even if enforcement costs are zero). Measuring these parameters is critical for evaluating the cost effectiveness of alternative policies. In this paper, we present plausibly causal estimates of the own-price elasticities of meth proxy demand in a setting in which enforcement costs are relatively low (at least relative to imprisonment of users and traffickers.)

First, we provide first arguably causal estimates of the own-price elasticity of meth proxy demand using instrumental variables and two separate measures of high risk consumption: hospitalization inpatient and drug treatment admissions. We show that meth demand curve is downward-sloping but quite inelastic. The own-price elasticity for drug treatment admissions is -0.13 to -0.21 and -0.24 to -0.28 for hospitalizations. Our estimates are similar in magnitude to those estimated by **?** and **?**, but smaller in magnitude to the central tendency across all estimates.

Second, our study shows that several state and federal interventions into precursor markets in the 1990s and 2000s created large shifts in supply, increased meth purity-adjusted prices, and reduced meth consumption. We find some evidence that these regulations caused an increase in cocaine use, but find no evidence that it increased alcohol, marijuana or heroin abuse. This makes sense given that both are stimulants. Precursor control when it disrupts input markets can cause large swings in retail street prices which in turn drives down high levels of meth addiction. Unfortunately, the policy experiment also showcases the limited value of regulating precursor access when there are substitutes for wholesale bulk precursor. The interventions caused prices to reach their peak after six months before returning to pre-treatment levels suggesting significantly higher long-run supply elasticities for meth. The lack of evidence for permanent increases in price may be due to substitution in the points of purchase in the precursor supply chain, such as retail pharmacies, and spatial substitution into regions without regulatory obstacles to overcome. A perfectly elastic long-run supply curve ultimately calls into question the cost-effectiveness of precursor control as a viable policy in the event that such regulations impose non-trivial costs on non-criminal consumption (e.g., Sudafed products).

Each subsequent intervention had a less disruptive effect on prices than the intervention before it. Had the 2006 CMEA law increased prices as much as the first 1995 federal ephedrine regulation had, then 2006 prices would've rose 258%.[23] Using an elasticity of -0.10, this would've reduced meth self admissions from 5.213 in early 2006 to 3.869, or 25.8%.

We can use our estimates with the model from **?** to determine whether quantity restrictions are likely cost-effective. Using an estimated own-price elasticity of meth proxy demand -0.20, precursor control would be optimal if the negative social marginal willingness to pay for meth was at least five times its private benefit to users (Equation **??**). Given recent evidence that the elasticity of foster care with respect to parental meth use is 1.54, it is possible that precursor control satisfies this condition (**??**). This back-of-the-envelope approach suggests that precursor control

[23] The 1995 federal intervention increased log prices 1.274 points, or $1 - e^{1.274} = 2.58$.

may dominate enforcement policies that rely on law enforcement to reduce drug supply given diminishing returns to prison and other costs associated with the "War on Drugs" (**?**).

The interventions studied in this paper only temporarily disrupted meth producers, so it is plausible that the these interdictions are sub-optimal if they are not implemented in such a way as to make block substitution away from the interdictions themselves. It remains to be seen if interdictions are cost effective in the long-run, and whether they can be implemented in a permanent way without major reductions in consumer welfare associated with reduced access to legitimate medicines. Some pharmaceutical drugs with large social costs may fit a similar regulation framework. For example, abuse of oxycodone, a semi-synthetic opioid analgesic, is the primary cause of a decade-long increase in overdose deaths in the US (**?**). Drugs like oxycodone require sophisticated production facilities (i.e., nonindustrial synthesis is difficult), have the potential for large social costs from abuse, but also have some legitimate medical uses. Lessons from meth precursor regulation may help inform regulation for a broad class of legitimate medicines. Given that prescription drug deaths have now surpassed motor vehicle deaths to become the leading cause of injury death in the US, policymakers would benefit from enhanced understanding of the regulatory challenges they face when targeting chemically synthesized addictive substances that also have considerable legitimate benefits to consumers (**???**).

Alternative policies which blocked illegal manufacturers of meth to pseudoephedrine without imposing unnecessary burdens on legitimate consumers of pseudoephedrine would be preferable, assuming such plausible policies exist. Technological solutions that make pseudoephedrine "tamper-proof" might be preferable from a social welfare perspective than purely regulatory solutions. Westport Pharmaceuticals developed a new sinus product from pseudoephedrine that reduced its usefulness for meth cooks without reducing its utility for consumers by inventing a tamper-resistant formulation that makes meth manufacture practically ineffective.[24] These approaches have the benefit of allowing selective access to precursor chemicals according to health needs and not criminal production. Finally, our analysis used proxies and while evidence suggests extremely addictive substances show up in proxies more often, more information on light consumers is needed to learn more about the entire demand curve.[25]

[24] See `http://zephrex-d.com/how-it-works`.

[25] For now, the best measure of meth use is the population of users associated with hospitalization and treatment admissions.

Appendix A Data appendix

We largely follow the methodology that **?** outline to prepare a series of meth prices. This report, which the authors prepare for the White House Office of National Drug Control Policy, examines the price trends for cocaine, heroin, cannabis, and meth in the US using prices from the Drug Enforcement Agency's System to Retrieve Information from Drug Evidence (STRIDE). We acquired STRIDE through a Freedom of Information Act request. STRIDE observations come from law enforcement events such as lab seizures, undercover purchases, etc. Samples are sent to DEA labs to identify the drugs and purities. Cocaine, heroin, and meth, occur sufficiently frequently to construct a price series. On the other hand, law enforcement officers collect most cannabis observations from seizures rather than purchases, and therefore it is not possible to construct a marijuana price series.

Following **?**, we keep US observations originating from undercover purchases, individual seizures, and lab seizures and drop observations with missing or nonsensical price, weight, or purity data. We link drug observations to a drug market analogous to a metropolitan statistical area. Observations outside of major metropolitan drug markets are assigned markets associated with Census divisions.

Each observation is assigned a market quantity or distribution level based on the net weight from the observation. For meth, we use three market quantities defined as having a net weight of less than ten grams, between ten and 100 grams, and more than 100 grams. For heroin, we use three market quantities with thresholds of 1 and 10 grams. For powder cocaine, we use four market quantities with thresholds of 2, 10, and 50 grams. For cocaine, we use three groups defined by thresholds of 1 and 15 grams. In this paper, we call meth, heroin, and cocaine observations retail if they come from the smallest two categories (i.e., less than 100 grams for meth, less than 10 grams for powder cocaine and heroin, and less than 15 grams for crack cocaine).

To time the interventions, we use a stepwise regression procedure using the following model:

$$\text{E}(\text{real price}_{ijk}) = \delta_0 + \tau_t + \tau_t^2 + \nu_{it}, \qquad \text{(A-1)}$$

where expected price is a variable of individual meth price observations, τ_t is a linear time trend common to all states, and τ_t^2 is a quadratic time trend common to all states. We start without any fixed effects for the intervention months. Stepwise, we add a single fixed effect for each month after the intervention. If the fixed effect is significant, we keep it in the model. We continue these steps until a post-intervention, contiguous-month fixed effect is no longer significant. Using this procedure, we obtain the intervention lengths.

Appendix B Composition of hospitalizations

Both interventions caused large increases in real, purity-adjusted meth prices. It is plausible that the observed reduction in quantity is due to changes in the composition of users during these episodes, as opposed to reduced consumption. Therefore, to check, we examined if population characteristics changed during each intervention.

Figure A-1 shows the aggregate mean age of inpatients in NIS by substance type from 1994 to 2001. Each series controls for seasonal trends by using predicted values from models that controlled for month-of-year fixed effects. Figure A-2 similarly presents aggregate mortality rates by substance type. Both figures agree that we can find no evidence for compositional shifts occurring around or during the interventions.

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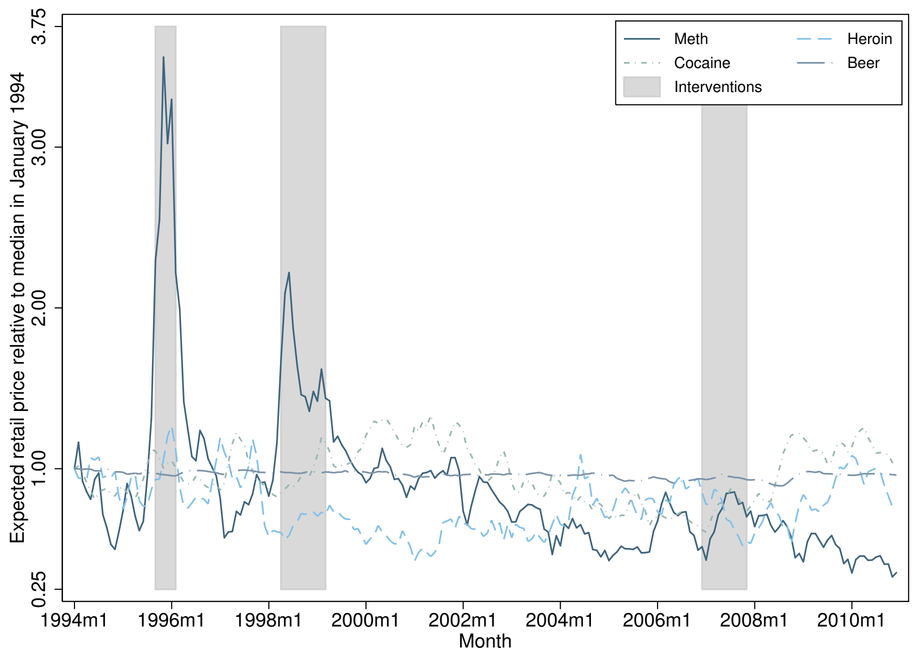
Figure 1: Ratio of median purities of meth, heroin, and cocaine relative to their respective values in January 1994, STRIDE, 1994–2010

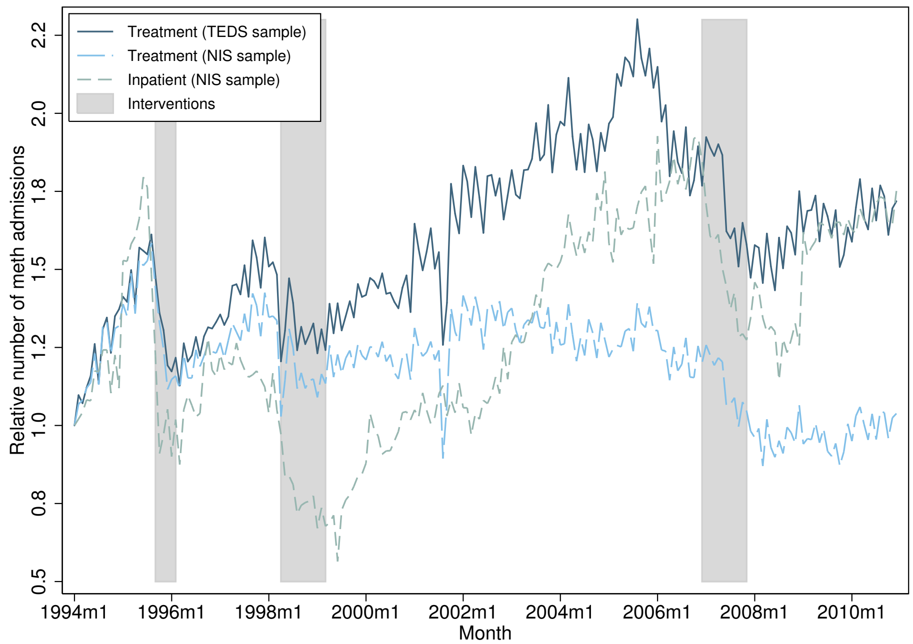
Notes: Authors' calculations from STRIDE. Month-of-year fixed effects have been partialled out from the raw series to improve presentation. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Figure 2: Ratio of median monthly expected retail prices of meth, heroin, and cocaine, and retail price of beer relative to their respective values in January 1994, STRIDE and ACCRA, 1994–2010



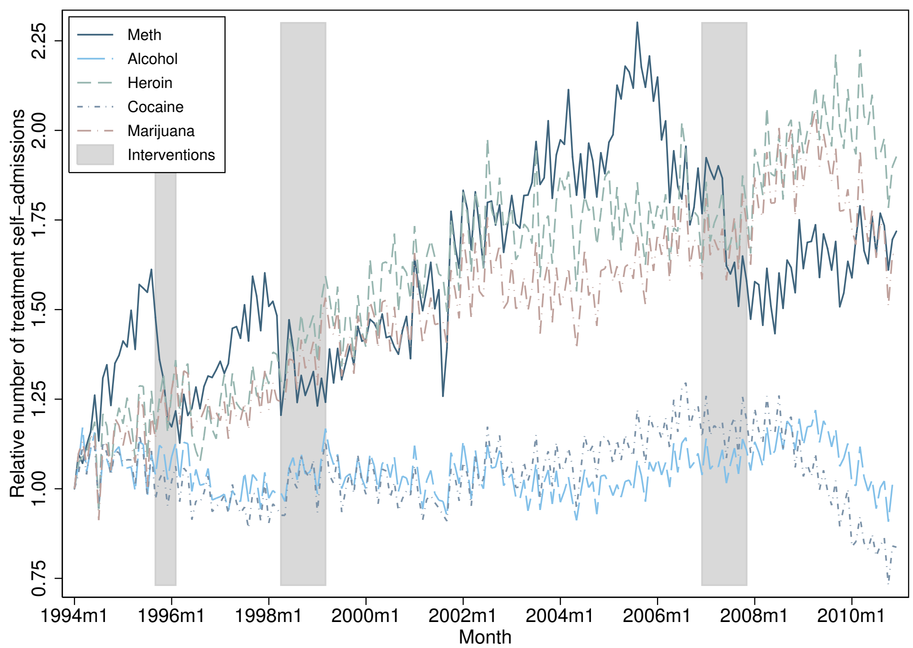
Notes: Authors' calculations from STRIDE and ACCRA. Month-of-year fixed effects have been partialled out from the raw series to improve presentation. Prices are inflated to 2013 dollars by the All Urban CPI series before calculating the ratio. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Figure 3: Hospital inpatient and self-admitted treatment proxies for meth use relative to January 1994, TEDS and NIS, various subsamples, 1994–2010



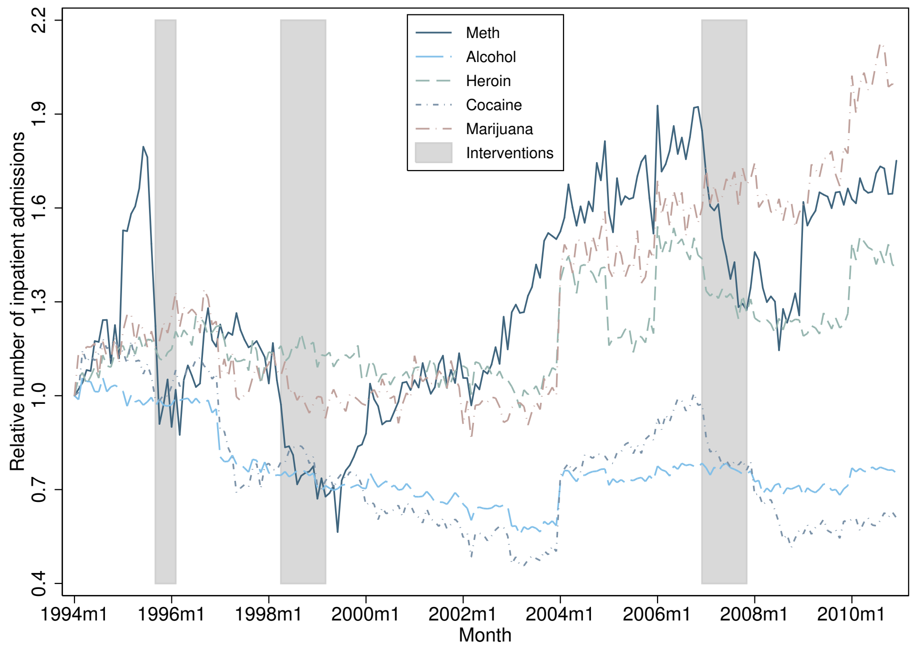
Notes: Month-of-year fixed effects have been partialled out from the raw series to improve presentation. The NIS sample includes only states that participated in the NIS during the entire sample period: Arizona, California, Colorado, Connecticut, Illinois, Iowa, Kansas, Maryland, Massachusetts, New Jersey, New York, Oregon, Pennsylvania, South Carolina, Washington, and Wisconsin. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Figure 4: Self-admitted treatment proxies for use of various drugs relative to January 1994, TEDS, states in TEDS sample, 1994–2010



Notes: Month-of-year fixed effects have been partialled out from the raw series to improve presentation. Arizona, the District of Columbia, Indiana, Kentucky, Mississippi, West Virginia, and Wyoming are excluded from the sample because of poor TEDS data quality during some or all of the sample period. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Figure 5: Hospital inpatient proxies for use of various drugs relative to January 1994, NIS, states in NIS sample, 1994–2010

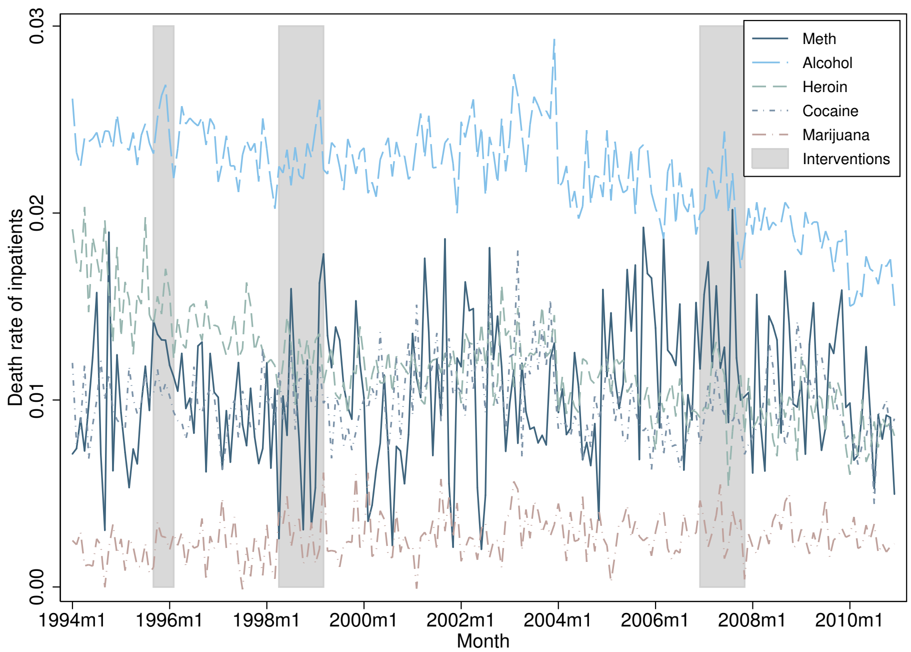


Notes: Month-of-year fixed effects have been partialled out from the raw series to improve presentation. The NIS sample includes only states that participated in the NIS during the entire sample period: Arizona, California, Colorado, Connecticut, Illinois, Iowa, Kansas, Maryland, Massachusetts, New Jersey, New York, Oregon, Pennsylvania, South Carolina, Washington, and Wisconsin. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Figure A-1: Mean age of inpatients reporting use of various drugs, NIS, NIS sample, 1994–2010

Notes: Month-of-year fixed effects have been partialled out from the raw series to improve presentation. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Figure A-2: Death rate of inpatients reporting use of various drugs, NIS, NIS sample, 1994–2010



Notes: Month-of-year fixed effects have been partialled out from the raw series to improve presentation. The 1995 and 1997 interdictions represent the windows of time during which real prices of a pure gram deviated from their pre-treatment level. The 2006 interdiction represents the window between the enactment and effective date of the Combat Methamphetamine Epidemic Act.

Table 1: Selected descriptive statistics, 1994–2010

Variables	Source	N	Mean	Std. dev.	Min.	Max.
Drug treatment proxies for drug use						
Meth admissions	TEDS	8,976	312	843	0	8359
Meth admissions, self-referred	TEDS	8,976	80	221	0	1903
Alcohol admissions	TEDS	8,976	2008	2788	0	21182
Alcohol admissions, self-referred	TEDS	8,976	730	796	0	5881
Cocaine admissions	TEDS	8,976	978	1736	0	13607
Cocaine admissions, self-referred	TEDS	8,976	240	367	0	2611
Heroin admissions	TEDS	8,976	558	1163	0	8487
Heroin admissions, self-referred	TEDS	8,976	74	146	0	1253
Marijuana admissions	TEDS	8,976	1011	1346	0	12101
Marijuana admissions, self-referred	TEDS	8,976	447	563	0	4872
Hospital inpatient proxies for drug use						
Meth admissions	NIS	2,892	53	119	0	782
Alcohol admissions	NIS	2,892	944	849	57	4326
Cocaine admissions	NIS	2,892	289	338	0	1857
Heroin admissions	NIS	2,892	322	355	3	2016
Marijuana admissions	NIS	2,892	151	158	3	897
Retail prices ($/pure g)						
Meth price	STRIDE	3,962	291	335	8	2912
Meth price, imputed	STRIDE	8,976	343	369	8	2912
Cocaine price	STRIDE	4,840	198	164	10	2749
Cocaine price, imputed	STRIDE	8,976	196	177	10	2749
Heroin price	STRIDE	2,845	941	1010	23	9930
Heroin price, imputed	STRIDE	8,976	877	845	23	9930
Retail prices ($)						
Liquor price	ACCRA	8,976	26.98	1.99	20.30	38.49
Beer price	ACCRA	8,976	6.30	0.85	3.74	11.62
Wine price	ACCRA	8,976	7.84	0.91	5.33	13.03
Controls						
Population aged 15–49 years (1,000s)	SEER	8,976	249	288	20	1734
Unemployment rate (%)	CPS	8,976	5.18	1.85	1.50	14.80
Cigarette tax ($/pack)	O&W	8,976	0.86	0.67	0.03	4.66

Notes: Authors' calculations. The level of variation is state by month. The TEDS sample excludes states with poor data quality during some or all of the sample period: Arizona, the District of Columbia, Indiana, Kentucky, Mississippi, West Virginia, and Wyoming. The NIS sample includes only states that participated in the NIS during the entire sample period: Arizona, California, Colorado, Connecticut, Illinois, Iowa, Kansas, Maryland, Massachusetts, New Jersey, New York, Oregon, Pennsylvania, South Carolina, Washington, and Wisconsin. Prices are inflated to 2013 dollars by the All Urban CPI series.

Table 2: Regressions of log self-admitted methamphetamine treatment and log hospital inpatient admissions on log drug prices, TEDS and NIS samples, 1994–2010

Outcome	Drug treatment						Hospital inpatient					
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log meth price (1 month lag)	−0.09***	−0.13**	−0.06***	−0.14**	−0.06***	−0.17***	−0.07	−0.27***	−0.09*	−0.26**	−0.09*	−0.28***
	(0.02)	(0.06)	(0.01)	(0.06)	(0.01)	(0.06)	(0.05)	(0.10)	(0.04)	(0.10)	(0.04)	(0.09)
Log unemployment rate	0.29**	0.27**	0.23**	0.19**	0.23**	0.17**	−0.25*	−0.34**	−0.07	−0.14	−0.09	−0.18
	(0.11)	(0.11)	(0.10)	(0.10)	(0.09)	(0.08)	(0.13)	(0.14)	(0.12)	(0.12)	(0.13)	(0.12)
Log cigarette tax	−0.02	−0.02	0.00	−0.01	0.03	0.02	0.02	−0.03	−0.12	−0.17**	−0.15**	−0.21***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.15)	(0.15)	(0.08)	(0.08)	(0.07)	(0.08)
Log population 15–49	1.59**	1.54**	2.44**	2.21**	4.66***	3.97***	0.09	−0.11	3.20***	3.01***	4.53***	3.93***
	(0.75)	(0.73)	(1.20)	(1.08)	(1.42)	(1.24)	(1.49)	(1.45)	(0.96)	(0.80)	(1.20)	(1.00)
Linear national trend	×	×					×	×				
Linear state trends			×	×					×	×		
Quadratic state trends					×	×					×	×
First stage												
Intervention indicator		0.47***		0.48***		0.48***		0.54***		0.54***		0.54***
(1 month lag)		(0.05)		(0.06)		(0.06)		(0.08)		(0.09)		(0.09)
First-stage F-statistic		75		73		71		41		36		34
First-stage p-value		0.00		0.00		0.00		0.00		0.00		0.00
Specification												
R^2	0.92		0.94		0.95		0.93		0.95		0.95	
N (state-months)	8,532	8,532	8,532	8,532	8,532	8,532	2,830	2,830	2,830	2,830	2,830	2,830
N (states)	44	44	44	44	44	44	15	15	15	15	15	15
Mean of dep. var.	3.99	3.99	3.99	3.99	3.99	3.99	3.73	3.73	3.73	3.73	3.73	3.73
Std. dev. of dep. var.	1.71	1.71	1.71	1.71	1.71	1.71	1.74	1.74	1.74	1.74	1.74	1.74

Notes: All models include state and month-of-year fixed effects. Standard errors that account for arbitrary, within-state heteroskedasticity are shown in parentheses. Stars indicate statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Regressions of log alcohol, heroin, cocaine, and marijuana outcomes on log drug prices, TEDS and NIS samples, 1994–2010

Drug	Alcohol				Heroin				Cocaine				Marijuana			
Outcome	Treatment		Inpatient		Treatment		Inpatient		Treatment		Inpatient		Treatment		Inpatient	
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log meth price (3 month lag)	−0.00	0.06	−0.01	−0.00	−0.02	0.08	−0.02	0.01	−0.01	0.10	−0.04**	−0.02	0.00	0.06	−0.03*	−0.06
	(0.02)	(0.06)	(0.01)	(0.04)	(0.03)	(0.09)	(0.01)	(0.06)	(0.02)	(0.08)	(0.02)	(0.10)	(0.02)	(0.06)	(0.02)	(0.08)
Log liquor price (1 month lag)	0.91	0.96*	0.31	0.33												
	(0.56)	(0.56)	(0.35)	(0.37)												
Log beer price (1 month lag)	−0.38**	−0.38**	0.21***	0.21***												
	(0.15)	(0.16)	(0.07)	(0.06)												
Log wine price (1 month lag)	−0.21	−0.19	0.34***	0.35***												
	(0.22)	(0.23)	(0.11)	(0.11)												
Log unemployment rate	0.12	0.14	−0.14	−0.13*	0.25***	0.29***	−0.03	−0.02	−0.03	0.01	−0.32**	−0.31***	0.17	0.19*	−0.06	−0.07
	(0.09)	(0.10)	(0.08)	(0.08)	(0.08)	(0.08)	(0.12)	(0.12)	(0.07)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)	(0.13)	(0.12)
Log cigarette tax	−0.09	−0.08	−0.12**	−0.12**	0.00	0.02	−0.17*	−0.16*	−0.04	−0.02	−0.14**	−0.13*	−0.10	−0.09	−0.18**	−0.18***
	(0.08)	(0.08)	(0.05)	(0.05)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.06)	(0.07)	(0.08)	(0.08)	(0.06)	(0.07)
Log population 15–49	−1.05	−0.55	1.98**	2.06**	−1.15	−0.39	2.11**	2.23**	1.31	2.13	5.83**	5.93***	−1.91	−1.50	3.01***	2.86***
	(1.48)	(1.49)	(0.75)	(0.87)	(1.21)	(1.21)	(0.92)	(0.93)	(1.49)	(1.62)	(1.97)	(2.26)	(1.81)	(1.84)	(0.95)	(1.08)
Log heroin price (1 month lag)					−0.00	−0.00	0.01*	0.01*								
					(0.01)	(0.01)	(0.01)	(0.01)								
Log cocaine price (1 month lag)									−0.06***	−0.07***	−0.07**	−0.07***				
									(0.02)	(0.02)	(0.03)	(0.03)				
Medical marijuana law (1 month lag)													−0.18***	−0.17***	0.06	0.05
													(0.04)	(0.04)	(0.16)	(0.16)
Quadratic state trends	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
First stage																
Intervention indicator		0.49***		0.53***		0.50***		0.54***		0.49***		0.54***		0.49***		0.54***
(3 month lag)		(0.05)		(0.08)		(0.06)		(0.09)		(0.06)		(0.09)		(0.06)		(0.09)
First-stage F-statistic		87		42		77		38		79		36		79		36
First-stage p-value		0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00
Specification																
R^2	0.87		0.96		0.94		0.95		0.91		0.94		0.88		0.93	
N (state-months)	8,685	8,685	2,847	2,847	7,973	7,973	2,847	2,847	8,648	8,648	2,846	2,846	8,681	8,681	2,847	2,847
N (states)	44	44	15	15	44	44	15	15	44	44	15	15	44	44	15	15
Mean of dep. var.	6.71	6.71	7.11	7.11	4.13	4.13	5.87	5.87	5.69	5.69	5.72	5.72	6.30	6.30	5.20	5.20
Std. dev. of dep. var.	0.97	0.97	0.87	0.87	1.71	1.71	1.13	1.13	1.20	1.20	1.15	1.15	1.03	1.03	0.99	0.99

Notes: All models include state and month-of-year fixed effects. Standard errors that account for arbitrary, within-state heteroskedasticity are shown in parentheses. Stars indicate statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Regressions of log self-admitted methamphetamine treatment and log hospital inpatient admissions on log drug prices, TEDS and NIS samples, 1994–2010

Outcome	Drug treatment						Hospital inpatient					
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log meth price (1 month lag)	−0.09***	−0.21***	−0.06***	−0.20***	−0.06***	−0.20***	−0.07	−0.24***	−0.09*	−0.25***	−0.09*	−0.26***
	(0.02)	(0.06)	(0.01)	(0.06)	(0.01)	(0.06)	(0.05)	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)
Log unemployment rate	0.29**	0.24**	0.23**	0.17*	0.23**	0.16**	−0.25*	−0.32***	−0.07	−0.14	−0.09	−0.17
	(0.11)	(0.11)	(0.10)	(0.09)	(0.09)	(0.08)	(0.13)	(0.12)	(0.12)	(0.11)	(0.13)	(0.11)
Log cigarette tax	−0.02	−0.02	0.00	−0.01	0.03	0.01	0.02	−0.02	−0.12	−0.17**	−0.15**	−0.21***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.15)	(0.15)	(0.08)	(0.08)	(0.07)	(0.07)
Log population 15–49	1.59**	1.44**	2.44**	2.03*	4.66***	3.77***	0.09	−0.07	3.20***	3.02***	4.53***	4.01***
	(0.75)	(0.71)	(1.20)	(1.05)	(1.42)	(1.24)	(1.49)	(1.44)	(0.96)	(0.80)	(1.20)	(0.96)
Linear national trend	×	×					×	×				
Linear state trends			×	×					×	×		
Quadratic state trends					×	×					×	×
First stage												
1995 intervention indicator		0.89***		0.90***		0.93***		0.99***		0.99***		1.05***
(1 month lag)		(0.13)		(0.12)		(0.13)		(0.21)		(0.22)		(0.21)
1997 intervention indicator		0.62***		0.61***		0.58***		0.65***		0.65***		0.64***
(1 month lag)		(0.05)		(0.05)		(0.06)		(0.07)		(0.07)		(0.07)
CMEA indicator		0.11**		0.12**		0.13**		0.12*		0.12*		0.08
(1 month lag)		(0.05)		(0.05)		(0.05)		(0.06)		(0.07)		(0.07)
First-stage F-statistic		90		65		45		41		37		32
First-stage p-value		0.00		0.00		0.00		0.00		0.00		0.00
Hansen χ^2-statistic		1.83		2.06		1.55		0.33		0.33		0.34
Hansen p-value		0.40		0.36		0.46		0.85		0.85		0.85
Specification												
R^2	0.92		0.94		0.95		0.93		0.95		0.95	
N (state-months)	8,532	8,532	8,532	8,532	8,532	8,532	2,830	2,830	2,830	2,830	2,830	2,830
N (states)	44	44	44	44	44	44	15	15	15	15	15	15
Mean of dep. var.	3.99	3.99	3.99	3.99	3.99	3.99	3.73	3.73	3.73	3.73	3.73	3.73
Std. dev. of dep. var.	1.71	1.71	1.71	1.71	1.71	1.71	1.74	1.74	1.74	1.74	1.74	1.74

Notes: All models include state and month-of-year fixed effects. Standard errors that account for arbitrary, within-state heteroskedasticity are shown in parentheses. Stars indicate statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Regressions of log alcohol, heroin, cocaine, and marijuana outcomes on log drug prices, TEDS and NIS samples, 1994–2010

Drug	Alcohol				Heroin				Cocaine				Marijuana			
Outcome	Treatment		Inpatient		Treatment		Inpatient		Treatment		Inpatient		Treatment		Inpatient	
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log meth price (3 month lag)	−0.00	0.02	−0.01	−0.00	−0.02	0.03	−0.02	−0.00	−0.01	−0.00	−0.04**	−0.04	0.00	0.02	−0.03*	−0.03
	(0.02)	(0.07)	(0.01)	(0.03)	(0.03)	(0.10)	(0.01)	(0.05)	(0.02)	(0.09)	(0.02)	(0.07)	(0.02)	(0.08)	(0.02)	(0.07)
Log liquor price (1 month lag)	0.91	0.93*	0.31	0.34												
	(0.56)	(0.55)	(0.35)	(0.35)												
Log beer price (1 month lag)	−0.38**	−0.38**	0.21***	0.21***												
	(0.15)	(0.15)	(0.07)	(0.06)												
Log wine price (1 month lag)	−0.21	−0.20	0.34***	0.35***												
	(0.22)	(0.23)	(0.11)	(0.12)												
Log unemployment rate	0.12	0.12	−0.14	−0.13*	0.25***	0.26***	−0.03	−0.02	−0.03	−0.03	−0.32**	−0.32***	0.17	0.18	−0.06	−0.06
	(0.09)	(0.10)	(0.08)	(0.07)	(0.08)	(0.09)	(0.12)	(0.11)	(0.07)	(0.08)	(0.11)	(0.10)	(0.11)	(0.11)	(0.13)	(0.11)
Log cigarette tax	−0.09	−0.08	−0.12**	−0.12**	0.00	0.01	−0.17*	−0.17**	−0.04	−0.04	−0.14**	−0.14**	−0.10	−0.10	−0.18**	−0.18***
	(0.08)	(0.08)	(0.05)	(0.05)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)	(0.08)	(0.08)	(0.06)	(0.06)
Log population 15–49	−1.05	−0.88	1.98**	2.08**	−1.15	−0.79	2.11**	2.18**	1.31	1.39	5.83**	5.79***	−1.91	−1.79	3.01***	3.02***
	(1.48)	(1.36)	(0.75)	(0.82)	(1.21)	(1.13)	(0.92)	(0.86)	(1.49)	(1.39)	(1.97)	(2.08)	(1.81)	(1.67)	(0.95)	(1.03)
Log heroin price (1 month lag)					−0.00	−0.00	0.01*	0.01*								
					(0.01)	(0.01)	(0.01)	(0.01)								
Log cocaine price (1 month lag)									−0.06***	−0.06***	−0.07**	−0.07***				
									(0.02)	(0.02)	(0.03)	(0.02)				
Medical marijuana law (1 month lag)													−0.18***	−0.18***	0.06	0.06
													(0.04)	(0.04)	(0.16)	(0.16)
Quadratic state trends	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
First stage																
1995 intervention indicator		0.92***		1.01***		0.93***		1.06***		0.92***		1.05***		0.92***		1.04***
(3 month lag)		(0.12)		(0.21)		(0.13)		(0.21)		(0.13)		(0.22)		(0.13)		(0.21)
1997 intervention indicator		0.59***		0.65***		0.58***		0.63***		0.57***		0.63***		0.58***		0.64***
(3 month lag)		(0.06)		(0.07)		(0.05)		(0.07)		(0.05)		(0.07)		(0.06)		(0.08)
CMEA indicator		0.14***		0.05		0.15***		0.09		0.15***		0.10		0.15***		0.09
(3 month lag)		(0.05)		(0.07)		(0.05)		(0.06)		(0.05)		(0.06)		(0.05)		(0.06)
First-stage F-statistic		44		36		49		31		51		31		44		27
First-stage p-value		0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00
Hansen χ^2-statistic		0.28		0.13		0.44		0.04		1.77		0.06		0.29		0.37
Hansen p-value		0.87		0.94		0.80		0.98		0.41		0.97		0.86		0.83
Specification																
R^2	0.87		0.96		0.94		0.95		0.91		0.94		0.88		0.93	
N (state-months)	8,685	8,685	2,847	2,847	7,973	7,973	2,847	2,847	8,648	8,648	2,846	2,846	8,681	8,681	2,847	2,847
N (states)	44	44	15	15	44	44	15	15	44	44	15	15	44	44	15	15
Mean of dep. var.	6.71	6.71	7.11	7.11	4.13	4.13	5.87	5.87	5.69	5.69	5.72	5.72	6.30	6.30	5.20	5.20
Std. dev. of dep. var.	0.97	0.97	0.87	0.87	1.71	1.71	1.13	1.13	1.20	1.20	1.15	1.15	1.03	1.03	0.99	0.99

Notes: All models include state and month-of-year fixed effects. Standard errors that account for arbitrary, within-state heteroskedasticity are shown in parentheses. Stars indicate statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A-1: Diagnosis codes used to identify inpatient drug users

Drug	ICD-9-CM code	Diagnosis description
Methamphetamine	3044	Amphetamine and other psychostimulant dependence
	3057	Amphetamine or related acting sympathomimetic abuse
	9697	Poisoning by psychostimulants
	E8542	Accidental poisoning by psychostimulants
	E9397	Psychostimulants causing adverse effects in therapeutic use
Alcohol	291	Alcoholic psychoses
	3030	Alcohol dependence syndrome
	3050	Nondependent alcohol abuse
	5711	Acute alcoholic hepatitis
	76071	Fetal alcohol syndrome
	7903	Excessive blood level of alcohol
	9773	Poisoning by other and unspecified drugs and medicinal substances
	980	Toxic effect of alcohol
	E860	Accidental poisoning by alcohol not elsewhere classified
	E9473	Other and unspecified drugs and medicinal substances causing adverse effects in therapeutic use
Cocaine	3042	Cocaine dependence
	3056	Nondependent cocaine abuse
	76075	Exposure to cocaine, perinatal
	9685	Poisoning by other central nervous system depressants and anesthetics
	97081	Poisoning by central nervous system stimulants
	E8552	Accidental poisoning by local anesthetics
	E9385	Surface and infiltration anesthetics causing adverse effects in therapeutic use
Heroin	3040	Opioid type dependence
	3047	Combinations of opioid type drug with any other drug dependence
	3055	Nondependent opioid abuse
	9650	Poisoning by analgesics, antipyretics, and antirheumatics
	E8500	Accidental poisoning by heroin
	E9350	Heroin causing adverse effects in therapeutic use
Marijuana	3043	Cannabis dependence
	3052	Nondependent cannabis abuse
	9696	Poisoning by psychodysleptics (hallucinogens)
	E8541	Accidental poisoning by psychodysleptics (hallucinogens)
	E9396	Psychodysleptics (hallucinogens) causing adverse effects in therapeutic use