Are Supply-Side Drug Control Efforts Effective? Evaluating OTC Regulations Targeting Methamphetamine Precursors

Carlos Dobkin, Nancy Nicosia, and Matthew Weinberg^{*}

August 23, 2013

Keywords: Anti-Drug Policy; Methamphetamine; Regulation; Public Health

Abstract

Enforcement efforts are the primary approach to reducing illegal drug use in the U.S., but evidence on their effectiveness is mixed. We provide new evidence on the effectiveness of enforcement efforts by using rich administrative records and the staggered implementation of state laws targeting over-the-counter medicines that can be used to produce methamphetamine. We estimate that the regulations reduced the number of methamphetamine laboratories operating in a state by 36%. We find no evidence of changes in methamphetamine consumption or drug related arrests, suggesting that people were able to find methamphetamine produced out of state.

1 Introduction

The most recent estimates indicate that the economic cost of drug abuse in the U.S. exceeds \$200 billion annually (ONDCP 2004). The majority of these costs are due to lost

^{*}The authors thank the Drug Enforcement Agency and the Substance Abuse and Mental Health Services Administration for providing data. We would also like to thank Joshua Angrist, Daniel Hosken, Diane Whitmore-Schanzenbach, Mark Stehr, and seminar participants at MIT, University of California at Berkeley, and University of California at Santa Cruz for helpful suggestions. Dobkin and Nicosia would like to acknowledge generous funding from the Substance Abuse Prevention Research Program at the Robert Woods Johnson Foundation. Finally, we appreciate the careful research assistance provided by Kristin Lang. Any mistakes are our own. Dobkin: UC Santa Cruz and NBER, cdobkin@ucsc.edu. Nicosia: RAND, nancy_nicosia@rand.org. Weinberg: Drexel University, mcw325@drexel.edu.

productivity (71%) with the remainder due to spending on the criminal justice system (20%) and health care (9%).¹ Government efforts to reduce the substantial costs to society of drug abuse fall into three categories: prevention, treatment, and enforcement. In fiscal year 2010, approximately \$1.5 billion, \$3.7 billion, and \$9.8 billion were allocated to these three areas, respectively (ONDCP 2010). Despite the fact that enforcement efforts are the primary approach to reducing drug use and its harms in the U.S., there is little consensus on the efficacy of typical enforcement efforts. Some studies find no impact of enforcement on prices (DiNardo 1993), others document a negative relationship (Yuan and Caulkins 1998), and still others a positive relationship (Miron 2003). This is likely due to the difficulty in implementing clean research designs when studying the effects of enforcement efforts against illegal drugs.

The evidence is somewhat more compelling for very large enforcement efforts. Several recent studies that have examined abrupt, plausibly exogenous, changes in enforcement efforts have provided evidence that enforcement can reduce illegal drug use and drug-related harms. A number of authors have documented that the reduction in heroin availability in Australia that resulted from the Taliban stamping out poppy production at least temporarily reduced some harms (Weatherburn, Jones, Freeman and Makkai 2002). Other authors have provided compelling evidence that the massive reduction in methamphetamine availability that occurred in the mid-1990s substantially (though temporarily) reduced drug related harms (Cunningham and Liu 2003), (Dobkin and Nicosia 2009), (Cunningham and Finlay 2013). Their findings are perhaps not surprising given that the reductions in drug availability examined in these studies are likely the largest and most abrupt to have occurred in any developed country in the past 40 years.

Estimates of the effects of very large enforcement efforts may be of little practical value in predicting the effects of the enforcement efforts policymakers typically consider implementing. The reason is that most enforcement efforts likely only moderately reduce the availability of the targeted drug. If modest reductions disproportionately impact the least addicted and criminally-involved users, then projections from the Australian heroin drought and the drastic reduction of available methamphetamine in the mid-1990's may be invalid. An additional concern about using the estimates from these two very large interventions is that they are identified largely from time-series variation and, consequently, provide limited insight into the persistence of enforcement efforts if other changes in the illicit drug market or national drug policy occurred subsequently.

¹A significant portion of the lost productivity is due to criminal activity as people who are incarcerated or pursuing criminal careers are typically not contributing significantly to the economy.

The objective of this study is to provide credible estimates of the impact of a smaller, but more typical enforcement effort than the ones examined in Cunningham and Liu (2003), Dobkin and Nicosia (2009), and Weatherburn et al. (2002). Specifically, we evaluate the impact of state restrictions on the sales of retail cold medicines that can be used to produce methamphetamine on the production and consumption of methamphetamine. Between 2004 and 2006, 35 states enacted laws regulating the sale of over-the-counter (OTC) cold medicines that contain pseudoephedrine or ephedrine, a key input in methamphetamine production.² These restrictions limited the amount of the products consumers could purchase, required consumers to show identification upon purchase, and forced retailers to keep a logbook of purchasers and place the products in a secure location. An evaluation of the effectiveness of these laws is important because they placed a burden on manufacturers, retailers, and legitimate consumers of cold medicines and because further restrictions have been passed or proposed in a number of states to make these products available only by prescription.

Two key features of the precursor regulations assist us in estimating their effect on illegal drug production and consumption. First, both the time period and geographical area affected by the laws are known and well-defined. Second, there is variation in the date that states enacted the laws. We exploit this variation to estimate the effects of the laws using newly-collected data on their enactment dates along with rich administrative datasets collected in the course of law enforcement, the provision of health services, and the establishment of workplace safety. One of our measures of methamphetamine production is drawn from the National Clandestine Lab Seizure System (NCLSS). These administrative data contain the location, discovery date, and production capacity of methamphetamine laboratories that were seized or discovered by law enforcement officials.³ Our other measures relating to production are the price and purity of methamphetamine purchased by

²States that did not implement their own legislation or implemented weak legislation became subject to the Combat Methamphetamine Enforcement Act (CMEA) of 2006.

³McBride, Terry-McElrath, Chriqui, O'Connor, VanderWaal and Mattson (2011) used three years of the NCLSS data (2004-2006) to study the effect of the OTC sales restrictions on methamphetamine labs only among states that adopted the regulations before October 1, 2005. The focus of their study was to measure the effects of different aspects of the laws (e.g. restrictions on quantity versus product placement) on methamphetamine labs only, while our goal is to more comprehensively assess the effects of the restrictions not only on production, but also on consumption and arrests. Our study also has three important strengths. First, our study includes every state and a longer pre- and post-period from January 2002 through March 2008. The longer post-period allows us to estimate any delayed responses to the laws, while a longer pre-period allows us to provide stronger evidence on the validity of our research design. Second, we include all states rather than only those who adopted early. And third, our models control more flexibly for common changes in outcomes across all states, which mitigates the risk of misattributing the effect of other changes in drug markets to the OTC regulations.

law enforcement officials. These measures are constructed from transactions in the Drug Enforcement Agency's System to Retrieve Information from Drug Evidence (STRIDE). Because there are no survey measures of drug use with sufficient variation and sample size to support our analysis, we employ proxies for consumption based on employee drug testing from Quest Diagnostics and from hospital inpatient drug testing from the Health Care Utilization Project's Nationwide Inpatient Sample and State Inpatient Datasets.⁴ Although these data are specific to particular populations, we document that they are strongly correlated with survey estimates of methamphetamine use in the general population and therefore provide useful proxies of overall drug use. Finally, we examine drug-related arrests using the FBI's Uniform Crime Reports. All of these datasets are sufficiently rich that, unlike the survey records in the literature, it is possible to estimate rates for each state on a monthly basis. Monthly estimates at the state level make it possible to take full advantage of the geographic and temporal variation in the implementation of these laws.

We examine the effect of the laws using a difference-in-difference model where the treatment is at the state level, with controls for state and month/year fixed effects and state-specific linear and quadratic time trends. In this model, identification requires that there are no state-level non-linear trends that are correlated with methamphetamine production and consumption and the introduction of the OTC restrictions. Our results are robust to adding controls for possible confounders. Graphical analyses of event study models support the validity of our main conclusions and also provide insight into the dynamic effects of the OTC restrictions on our outcomes of interest.

Implementing restrictions on the sales of OTC medicines significantly decreased the within-state production of methamphetamine. Given the negative externalities associated with the production of methamphetamine, this represents a policy success in itself. We estimate that the laws caused a 36 percent reduction in the number of methamphetamine laboratories. The reduction was largest for smaller laboratories with limited production capacity, but we find evidence of reductions for larger laboratories as well. Because the laws caused the largest reduction in smaller labs, we estimate overall domestic production of methamphetamine was reduced by about 25 percent because of the regulations. However, despite the disruption of domestic methamphetamine production, we find no evidence of an increase in the quality-adjusted price. Next, we document that the laws did not result in a significant change in methamphetamine consumption as proxied by

⁴When an admission record includes a mention of amphetamine use it is typically the result of a positive drug test but in some cases may be solely due to the patient's report of their own drug use.

positive workplace drug tests and hospital toxicology tests. Lastly, we find no evidence of a change in the arrest rate for possession or sales of dangerous non-narcotics. Our result that the laws reduced the number of domestic methamphetamine laboratories but left consumption unchanged suggests that people were able to obtain methamphetamine produced outside of their state of residence. This is consistent with evidence from the Drug Enforcement Agency that methamphetamine imports from Mexico increased around the time the laws were enacted.

The remainder of the paper is organized as follows. Section II provides background on the production and physiological effects of methamphetamine and on the efforts to reduce its availability. The administrative data sources used in this study are described in Section III. In Section IV, we describe our empirical strategy. Section V presents our findings with respect to production, consumption and arrests. Finally, we conclude with a discussion of the policy implications of our findings.

2 Background on Methamphetamine and Precursor Legislation

Methamphetamine is a central nervous system stimulant that induces a state of pleasure, high energy, and alertness that can last for up to 12 hours. The effects of methamphetamine are similar to those of cocaine but substantially longer lasting. For some users, methamphetamine use and withdrawal are associated with a number of adverse physical and psychological events including cardiovascular complications, premature mortality, mood disorders, cognitive impairment, risk-taking and aggressive behaviors (NIDA (2002); Rawson, Huber, Brethen, Obert, Gulati, Shoptaw and Ling (2001); Simon, Domier, Sim, Richardson, Rawson and Ling (2001); Lynch, Kemp, Krenske, Conroy and Webster (2003); ONDCP (2006); SAMHSA (2008)). In 2005, methamphetamine use was associated with nearly 1000 deaths in the U.S. and more than 169,000 individuals sought treatment for methamphetamine or amphetamine addiction.⁵ Some researchers and many law enforcement agencies have also suggested that methamphetamine use causes both property and violent crime (e.g., see Lynch, Kemp, Krenske, Conroy and Webster (2003)).

Manufacturing methamphetamine is a relatively simple, but potentially hazardous

⁵Death counts are derived from CDC tabulations of the Multiple Cause of Death file provided to the authors and are likely substantially biased downwards due to miscoding. Based on the Treatment Episode Dataset, methamphetamine accounts for the vast majority of drug treatment admissions for psychostimulants. See www.oas.samhsa.gov/2k8/methamphetamineTX/meth.pdf (Last accessed December 18, 2012).

process that produces toxic byproducts damaging to the environment. Unlike most other illicit substances, methamphetamine is a synthetic product whose critical precursors namely, ephedrine or pseudoephedrine - require a complex large scale industrial process to manufacture. Because of the concentration in the production of ephedrine and pseudoephedrine, legislation aimed at reducing their diversion to methamphetamine production has the potential to reduce methamphetamine availability. In the last 25 years, the federal government has passed several laws intended to reduce the diversion of ephedrine and pseudoephedrine to illegal drug labs. The first of these was the Chemical Diversion and Trafficking Act of 1988 (CDTA), which regulated ephedrine and pseudoephedrine in bulk powder form, but left processed forms unregulated.⁶ This was followed by the Domestic Chemical Diversion Control Act of 1993 which placed restrictions on OTC ephedrine products (e.g. tablets) and increased DEA oversight of suppliers. Then, the Methamphetamine Control Act of 1996 tightened regulations on the sale of products containing methamphetamine precursors over 24 grams, but contained an exception for "blister packs".⁷ Shortly thereafter, the Methamphetamine Anti-Proliferation Act of 2000 lowered the thresholds from 25 to 9 grams, but blister packs remained exempt. Each of these federal efforts induced methamphetamine producers to switch to sources of precursors that remained unregulated. Among their innovations was exploiting legitimate OTC consumer medicines containing methamphetamine precursors to support domestic production of methamphetamine (CRS 2007). Because many domestic labs turned to these OTC consumer products, states began instituting controls on OTC cold and sinus medications such as Sudafed and Tylenol Cold to deter their diversion as early as 2004. Federal legislation followed in the Combat Methamphetamine Act (CMEA) of 2005, which became effective in 2006.

The state and federal restrictions on OTC medicines containing methamphetamine precursors are the focus of our study. As shown in the last column of Table 1, thirtyfive states passed laws restricting the sales of OTC medicines beginning in January 2004. Then, the fifty states and the District of Columbia became subject to elements of the federal legislation regulating the sale of OTC medicines, which became effective in April and September 2006.

The most common state restrictions involved sales limits and product placement. Thirty-five states imposed limits on the sale of these products and required that they

 $^{^{6}}$ Other inputs were also regulated by these and other regulations, but we focus here on the history of ephedrine and pseudoephedrine regulations as they are most relevant for this study.

⁷The act also imposed monthly reporting requirements for "mail order" firms dealing in precursor chemicals.

be placed out of customers' reach behind the counter or in a locked cabinet in order to deter theft. The majority of states also required that purchasers present identification and twenty-four states required that retailers maintain a logbook in order to prevent people from subverting the laws by making repeated purchases. We recorded the date when each of these four restrictions went into effect in each state.⁸ The federal Combat Methamphetamine Act imposed sales restrictions in April of 2006 and as of September 2006 required purchasers to present identification and required retailers to keep products in a secure location and maintain a logbook. Table 1 presents the correlation between these various laws within a state and month which reveals that they are highly correlated.

Figure 1 shows the time series of implementation for the four most common components of the laws. Purchase limits were typically an early component and were often bundled with restrictions intended either to deter theft or prevent people from working around the sales limits by making repeated purchases. Our analyses focus on the timing of the earliest component - that is, the date at which each state first implemented any of the four restrictions described above. Similarly, we code the effective date of the federal law as April of 2006.

3 Data

Because of the rapid rate of implementation across states, this study relies on highfrequency administrative data sources to document the effects of the precursor regulations. We collected data on the number of methamphetamine labs, the price and purity of methamphetamine, positive drug tests for amphetamine among workers and among individuals admitted to the hospital, and drug-related arrests. While some of these datasets were collected by state and federal agencies at the individual- or transaction-level, we use them to construct monthly measures for each state.

We have three measures that allow us to examine the impact of these regulations on drug production, namely the number of labs identified by law enforcement, methamphetamine purity, and the nominal price of methamphetamine. The National Clandestine Lab Seizure System (NCLSS) contains information on labs seized or discovered by law enforcement.⁹ This dataset contains estimates of each site's production capacity, which is

⁸We compared summaries of state legislation from the National Association of Chain Drug Stores, Office of National Drug Control Policy and National District Attorney's Association with the text of legislation from the 50 states and the District of Columbia. We resolved any inconsistencies by examining the text of the laws. In a few cases a Board of Pharmacy rule or executive order preceded the state and federal legislation.

⁹A lab seizure is defined as "an illicit operation consisting of a sufficient combination of apparatus and

a critical measure in determining whether OTC regulations disproportionately impacted smaller labs. We rely on the Drug Enforcement Agency's System to Retrieve Information from Drug Evidence (STRIDE) to estimate the nominal prices and purity of methamphetamine.¹⁰ The STRIDE data have been criticized (Horowitz 2001), but remain the best source of information on the purity and price of methamphetamine in the U.S. These data record the date, location, method of acquisition (e.g., seizure, purchase, etc.), purity of the drug as determined by DEA labs, and, in the case of purchases, the price. We construct our price and purity measures using only observations on purchases (e.g., excluding seizures) in order to generate price and purity estimates from a consistent sample.

Estimating the share of the population that consumes methamphetamine and the frequency of their consumption is complicated due to its illicit nature. Surveys such as the National Survey on Drug Use and Health (NSDUH) at best provide noisy annual measures of drug use that are of little use when leveraging changes in state laws that occurred over a short time period of just a couple of years. It is also likely that consumption rates estimated from survey self-reports are biased downwards. For this reason, we measure methamphetamine consumption using drug testing data from Quest Diagnostics and the Health Care Utilization Project (HCUP). Quest Diagnostics is the largest provider of workplace drug tests. The rate of positive drug tests for amphetamine among employees tested by Quest Diagnostics is arguably a useful proxy for population wide drug use.¹¹ Unfortunately, we only have data on positive drug tests among employees from January 2000 until April 2006 and so we are unable to follow late adopters for a full year.¹² For a longer perspective on a larger sample of individuals, HCUP provides information on hospital admissions. These data allow us to identify hospital admissions (for any cause) that tested positive for amphetamine, which can be interpreted as a proxy for consumption. We rely primarily on HCUP's Nationwide Inpatient Sample (NIS), which is a sample of hospital admissions for up to 37 participating states from January 2000

chemicals that either has been or could be used in the manufacture or synthesis of controlled substances." The NCLSS also records 1) "seizure of only chemicals, glassware, and/or equipment normally associated with the manufacturing of a controlled/illicit substance" and 2) locations "where discarded laboratory equipment, empty chemical containers, waste by-products, pseudoephedrine containers, etc., were abandoned/dumped." See: $http: //www.michigan.gov/documents/EPIC143InstrNew_131649_7.doc$ (Last accessed December 29, 2012.)

¹⁰We have records from STRIDE and NCLSS for the period from January 2000 to March 2008.

¹¹We cannot differentiate amphetamines from methamphetamines in the drug testing and hospital data, but we do know from the TEDS data that more than 90% of the amphetamine abused in the U.S. is methamphetamine.

¹²These data were drawn from the ONDCP (2006) publication entitled "Pushing Back Against Meth". We attempted to obtain additional state-level data directly from Quest Diagnostics to extend our analysis period, but were unsuccessful.

to December 2007. To increase the precision of our estimates, we supplemented the NIS data with the State Inpatient Dataset for January 2000 through December 2007 for the states of Arizona, New Jersey, Washington, and Iowa.¹³

To examine the link between the OTC regulations and drug related arrests we use the Uniform Crime Reports (UCR). For the period from January 2000 to December 2007 we generate arrest rates for the possession and sale of illegal drugs for each state and month. The UCR is based on reports provided to the FBI by individual police agencies. While it is requested that agencies report monthly, many do not as reporting is voluntary. We drop observations from Alabama and Illinois because agencies in these states did not report on a monthly frequency.¹⁴

4 Empirical Strategy

Our empirical strategy exploits the variation in the timing of states' implementation of OTC regulations documented in Figure 1. Because of the fairly rapid pace of implementation and because many states adopted laws in the middle of the year, the unit of observation is a state-month. We provide both graphical and regression-based evidence on how these restrictions impacted production, consumption and arrests.

We begin with a descriptive graphical analysis by plotting the average of each measure of methamphetamine production, consumption, and drug-related arrests over the sample period. These figures show changes in average state methamphetamine production and consumption over the time period in our study. In each figure we plot the fraction of the U.S. population covered by any OTC sales restriction to document whether changes in outcomes occurred concurrently with enactment of the regulations.

After examining national trends in the outcomes over the sample period, we then implement a regression analysis. The regression analysis leverages the variation in the timing of state OTC regulations to separately identify the effects of the regulations from common changes in outcomes across all states. For each outcome, the regressions are estimated using data beginning in January 2002. The end dates vary across data sources as described in Section III and in the notes at the bottom of the regression tables. We fit

¹³Data from Iowa were only available for January 2004 through December 2007.

¹⁴In several other states there were large spikes across all arrest categories typically in June and December. These increases are likely due to a share of agencies reporting twice a year instead of monthly. In these cases, we replaced the outlier with the value in the preceding month within that state. Details are available upon request.

the following equation to the data using OLS:

$$Y_{st} = \beta OTC_{st} + \alpha_s + \gamma_t + \epsilon_{st} \tag{1}$$

where Y_{st} is the outcome in state s and time t. The variable of interest OTC_{st} is an indicator set to zero in the months prior to implementation of the state's regulation, one afterwards, and the fraction of the month a regulation was implemented in months a regulation was enacted.¹⁵ Given the strong correlation in when states adopted the different components of the laws, we define the OTC variable based on the earliest effective date for the four major retailer and consumer restrictions. We control for period-specific shocks common to all states by including a fixed effect for month/year γ_t and we control for unobservable time-invariant differences across states by including a fixed effect for each state α_s . The coefficient of interest β measures the effect of the OTC regulation on the average outcome. When the outcome Y_{st} is a state average, we weight the data to improve the efficiency of our estimates. The exact weights we use vary by outcome so we discuss them in Section III and the footnotes of the tables. We allow for serial correlation within a state and different variances in the error term across states by clustering our standard errors by state. We then expand on Model 1 by progressively adding statespecific linear and quadratic time trends and time-varying covariates that include the state unemployment rate, number of households receiving food stamps, average temperature and average precipitation.¹⁶

Our results from Model 1 are supported by event-study analyses that examine the timing of any change in each outcome. A key assumption necessary for specification 1 to estimate the effect of the regulation is that there are not unmeasured non-linear state specific trends correlated with the enactment of the regulations. The event study analysis allows us to examine any "pre-trend" that would raise concerns about our identification strategy and also allows us to determine how long it took the regulations to have any impact. We implement the event study by estimating the following equation with OLS:

$$Y_{st} = \sum_{j=-12}^{24} \pi_j 1(\tau_{st} = j) + \alpha_s + \gamma_t + \delta_s * t + \epsilon_{st}$$
(2)

where τ_{st} measures the month relative to the introduction of an OTC regulation, defined

¹⁵If a state law was enacted on the 15th of February of 2005 OTC_{st} would be coded as $\frac{28-14}{28} = .5$ during that time period for that state, for example.

¹⁶Previous research has shown that there is an effect of unemployment (Raphael and Winter-Ember 2001) and weather on crime (Jacob, Lefgren and Moretti 2007).

so that $\tau_{st} = 0$ if state *s* enacted an OTC regulation at any point in month *t*. We include state-specific linear time trends in order to mitigate the risk of OTC regulation endogeneity. We then produce graphs by plotting the estimated π_j coefficients with respect to event time, where the coefficients are measured relative to the month before an OTC restriction was put into place ($\tau_{st} = -1$).¹⁷ We present the implied pre-trend and its standard error in each of the event-study figures. These were calculated by regressing the coefficients on each of the 12 dummies corresponding to periods before a law was introduced on a linear trend in event time. The standard error of the slope estimate was calculated by applying the delta method to the OLS estimate of the slope in order to account for the first-step in the estimation procedure.

5 Results

In this section, we present our analysis of the impact of the laws regulating OTC medicines on methamphetamine production, consumption, and drug-related arrests. We begin by examining how the laws affected the number of discovered domestic laboratories as well as the price and purity of methamphetamine purchases. We then document the extent to which the laws affected consumption as measured by drug testing among workers and hospital admissions. Finally, we examine whether the intervention reduced arrest rates for the sale and possession of illegal drugs.

5.1 Methamphetamine Production

The intent of the OTC regulations is to prevent the diversion of over-the-counter medicines containing pseudoephedrine or ephedrine to the production of methamphetamine. Most recipes for methamphetamine require pseudoephedrine or ephedrine in combination with numerous other ingredients.¹⁸ Restricting access to these over-the-counter sources can affect the supply of methamphetamine in two ways. It can limit the number of producers with access to sufficient precursors to produce methamphetamine. Second, it can change the quality of available methamphetamine. Quality of methamphetamine will be reduced to the extent that the restrictions force producers to dilute their product or turn to inferior precursors which result in a less pure product. Alternatively, the quality of available methamphetamine may increase if the restrictions reshuffled production from lower quality

¹⁷This was done by subtracting our estimate of π_{-1} from each of the event period coefficients.

¹⁸Unlike ephedrine and pseudoephedrine, the other ingredients have numerous substitutes that have many legitimate uses and so are widely available.

producers to higher quality producers. We find evidence that limiting the availability of over-the-counter sources of pseudoephedrine reduces the number of producers with access to sufficient precursors to produce methamphetamine. We find no evidence that the precursor regulations led to lower-purity methamphetamine.

The ideal dataset for measuring the effect of the laws on methamphetamine production would be a census of labs for each state spanning a period before and after the laws went into effect. Given that methamphetamine producers have a strong incentive to hide their operations, this is clearly infeasible. As an alternative, we examine data on the number of labs that come to the attention of law enforcement agents. The number of labs discovered each month is an unknown fraction of the total number of labs in operation that month. This detection probability is likely a function of a number of factors including (among others) the effort of the law enforcement agents, the likelihood of a lab catching fire, and reports from the public. The relationship between the percentage change in the number of discovered labs and percentage change in the number of labs in operation is given by the following equation:

$$\frac{D_{post} - D_{pre}}{D_{pre}} = \frac{p_{post} - p_{pre}}{p_{post}} \left(1 + \frac{Labs_{post} - Labs_{pre}}{Labs_{pre}}\right) + \frac{Labs_{post} - Labs_{pre}}{Labs_{pre}} \tag{3}$$

where D is the number of labs detected, Labs is the number of labs in operation, p is the probability of detection, and the subscripts denote whether the period under consideration is before or after the implementation of the OTC law. If there is not a large change in the detection probability when the OTC regulations are put in place, the percentage change in the number of discovered labs is a good estimate of the percentage change in the number of labs in operation. In fact, if $p_{post} = p_{pre}$, then the percent change in the number of labs discovered is identical to the percent change in the number of labs in operation. There is anecdotal evidence that the OTC laws may have slightly increased the probability that a given lab will be detected as some police departments found cause to visit residences of people whose names appeared repeatedly in OTC sales logbooks. If the probability of a lab being detected increases with the law $(p_{post} > p_{pre})$, then using the percent change in the number of labs in operation will lead us to underestimate the reduction in labs by $100 * (\frac{p_{post} - P_{pre}}{p_{pre}})(1 + \frac{Labs_{pre} - Labs_{pre}}{Labs_{pre}})$ percentage points.¹⁹

¹⁹To get a sense of the possible scale of the bias consider the case where the OTC laws reduce the number of labs in operation by 50 percent and increase the probability of detection by 10 percent. Using the change in the number of labs detected will lead to an estimate of 45 percent which underestimates the change in the number of labs active by 5 percentage points.

In Figure 2, we present the average number of labs discovered across all states for each month. The labs have been split into three groups based on their estimated production capacity measured as the amount of methamphetamine that could be produced in a single production cycle. Two facts emerge from the figure. First, for each group, the figure shows a clear decrease in the average number of labs discovered beginning in early 2004. Second, by 2007 the average number of labs discovered in a state had reached less than half of what it was before 2004 for each of the three groups of labs. Comparing Figure 1 to Figure 2 makes it clear that not all of the decline in the number of labs from 2004 to 2007 can be attributed to the OTC regulations. The decline began prior to the time period when states enacted the sales restrictions. This motivates our regression approach, which exploits variation in the timing of state laws to estimate their impact.

Figure 3 presents the event study created by estimating Model 2. The dependent variable is the number of labs discovered in a state. The figure shows that the reduction in the number of labs was not entirely due to common reductions in labs discovered across all states. There is no evidence of a pre-trend for any of the outcomes during the twelve months preceding the enactment of an OTC regulation, rasing confidence in the validity of our identification assumption.

The corresponding regressions are presented in Table 2. Column 1 presents our most parsimonious model corresponding to equation 1, the second column adds state-specific linear time trends and corresponds to the more flexible version of the model used to construct the event study in Figure 3, the third column adds quadratic state-specific time trends, and the final column adds the covariates. The findings from the event study are confirmed by the regressions. Across specifications, the laws led to a reduction in the number of labs discovered. Column 2 of the first panel indicates a decline in the total number of discovered labs of approximately $36 \left(\frac{-5.05}{13.9}\right)$ percent. The other three panels present the estimates of the decline broken out by the size of the lab. The reduction was large for labs with capacity less than two ounces and labs with capacity between two and eight ounces at approximately 32 and 54 percent. For the largest labs the reduction was somewhat smaller at 22 percent and not significant at the .05 level.²⁰

The OTC regulations clearly reduced the average number of discovered methamphetamine labs in a state. Using these estimates of the reduction in the number of

 $^{^{20}}$ Our results are qualitatively unchanged if the dependent variable is measured as log(1 + NumberLabs). Our results are also unchanged if we explicitly model the number of labs as count data and estimate specification 1 using a poisson model estimated by maximum likelihood. However, the optimization algorithm we used to maximize the poisson model's likelihood function failed to converge once we included both linear and quadratic state-specific trends. We present these results in Appendix 1.

labs from Model 1 and the average number of labs before the restrictions were in place, we estimate the effect of the regulations on a state's methamphetamine production capacity. While this analysis ignores production in labs outside of the United States, it allows us to summarize the total reduction in domestic production capacity with one number. Our data contains information on the number of labs discovered by state and month for labs grouped in six different production capacity intervals: labs with capacity less than two ounces, between two and eight ounces, eight ounces and one pound, two pounds and nine pounds, ten pounds and nineteen pounds, and labs with capacity of at least twenty pounds. We estimate the total reduction in production capacity is first expanding on the results presented in Table 2 by estimating the reduction in the number of labs for all six lab size groups.²¹ The change in detected lab capacity is calculated by assigning the midpoint of the capacity lab sizes. Our estimate of the percent reduction in productive capacity is given by the following expression:

$$PercentCapacityReduction = \frac{\sum_{j=1}^{6} \beta_j * Capacity_j}{\sum_{j=1}^{6} E[DiscoveredLabs|PreOTC, Capacity_j] * Capacity_j}$$
(4)

where β_j is an estimate of the reduction in the number of labs in group j,

 $E[DiscoveredLabs|PreOTC, Capacity_j]$ is the average number of discovered labs in group j conditional on no OTC restriction being in place, and $Capacity_j$ is the midpoint of the productive capacity interval for group j.²² If the detection probability is the same across labs of different sizes and there is not a large change in the detection probability when the OTC regulations are put in place, this is a good estimate of the percentage change in productive capacity.

We estimate that the OTC restrictions reduced total methamphetamine production capacity within a state by 26 percent. Our results are fairly robust to using measures of the capacity of each group of labs other than the midpoint. If we measure the lab capacity at the 25th percentile instead of the midpoint, the estimated overall decline shrinks to 23 percent. Measuring capacity at the 75th percentile of each capacity interval increases the estimated decline to 28 percent. If we set the statistically insignificant estimates of the effect on larger labs to zero and use the midpoint of each range as the capacity, the estimated decline in capacity is 17 percent. While reducing the number of laboratories in the U.S. is in itself a policy success given the damaging effects of methamphetamine production on the environment and health, these labs may have accounted for only a small

 $^{^{21}\}mathrm{The}$ results are presented in the Appendix 2.

 $^{^{22}}$ We evaluate the capacity of labs in the largest group at the left endpoint of twenty pounds.

share of domestic consumption. It is also possible that any reduction in locally-produced methamphetamine may have been offset by an increase in methamphetamine imported from producers located outside of the state. Based on seizure data, the DEA estimated that domestic labs with capacity to produce less than 10 pounds accounted for only 35% of methamphetamine consumed in the U.S. in 2004, while seizures along the southwest border, likely to be imports from Mexico, account for the majority (53%) (ONDCP 2005). Perhaps even more relevant is the DEA's conclusion that "the ratio may be moving back in the direction of an approximate 80/20 breakdown of superlab supply to [small toxic lab] supply" and that an "associated dynamic appears to be the move of those superlabs to outside our country" (ONDCP 2005).

We next estimate the impact of the OTC restrictions on the purity and price of methamphetamine. Prior work (Dobkin and Nicosia 2009) documented that a very large, sudden, and unexpected reduction in the availability of a precursor led to a temporary reduction in the purity of methamphetamine and an increase in its price. Figure 4 documents changes in the average nominal price per gram and purity of methamphetamine over our sample period. We weight both series by the number of transactions used to compute the average outcome in each state and month. This reduces the volatility in the series and increases the precision of our estimates. There is no clear shift in the nominal price per gram at any time between 2002 to 2008. While there is a large drop in the average purity of methamphetamine at the end of 2005 implying an increase in the real (purity-adjusted) price of methamphetamine, there are also other large changes in average purity prior to the time period when states were enacting the regulations.

Figure 5 presents the event study for price and purity and Table 3 displays estimates from the corresponding regressions. The figure shows no clear pre-trend for either outcome, and the implied trend is not significantly different from zero at the 10 percent level. The figure also shows no increase in the nominal price of methamphetamine. The purity measure if anything increases after the introduction of the OTC regulations. The regressions confirm the event study. The point estimates imply a change in the average price per gram ranging from 2.89 to -1.83, depending on specification. This is quite small relative to the pre-intervention mean of 49 dollars per gram. Across specifications, none of these estimates are significant at conventional levels. We estimate small increases in the purity of methamphetamine of between 7 and 10 percent of the pre-regulation average purity level, though the estimates are only significant at the 10 percent level in the three specifications that control for state-specific trends. As expected, there is no evidence of changes in the price or purity of cocaine, crack, or heroin. The reduction in the number of labs discovered is compelling evidence that state OTC regulations disrupted local production of methamphetamine. The extent to which this disruption in methamphetamine production within a state affects consumption depends on how much of the methamphetamine consumed in a state is locally-produced as opposed to imported from other states or countries (e.g. Mexico) and how rapidly producers from other regions mobilized to meet the unfilled demand.

5.2 Methamphetamine Use

The reduction in the number of domestic labs may have increased the search costs of obtaining methamphetamine. In this section, we analyze the impact of the OTC restrictions on two measures of methamphetamine consumption: the rate of positive drug tests in the workplace and in hospital toxicology. The workplace drug test data arguably measures methamphetamine use amongst the most functional methamphetamine users, and the hospital admissions data likely measures methamphetamine use among more strongly addicted users.²³ We find no evidence that the laws reduced the rate of positive drug tests among either population.

Documenting the effect of the OTC regulations on methamphetamine consumption is challenging because consumption is an illegal activity. Given that we implement a stateby-month panel approach, we would ideally have monthly measurements of the share of the population consuming methamphetamine in each state and how much they are consuming. Surveys are of little use because of their limited sample sizes and infrequent nature (e.g. annual) and because the low prevalence of methamphetamine consumption makes it difficult to generate precise month-by-state series. A second issue with survey data is that relying on self-reports will probably result in consumption estimates that are substantially biased downward as there is substantial evidence that people underreport undesirable behaviors.²⁴

Fortunately, drug tests provide an alternative measure of methamphetamine consumption. The half-life of methamphetamine in the body is 9-12 hours and urine tests will typically return a positive test if the person consumed methamphetamine in the prior 3 to 5 days. Though the detection window is sensitive to the amount consumed given the

 $^{^{23}}$ Kelly and Rasul (2012) also use drug-related hospital admissions to study the effects of depenalizing cannabis in a borough of London on hospital admissions related to the use of hard drugs.

²⁴Stockwell, Zhao, Chikritzhs and Greenfield (2008) compare survey reports of alcohol consumption with estimates of alcohol sales from tax records and documents that alcohol consumption in surveys is underreported by over 50 percent. Survey measures likely underreport methamphetamine consumption by an even greater extent as it is even more stigmatized.

relatively short half life, even a 50 percent reduction in the amount of methamphetamine consumed should only reduce the period over which the use can be detected by 9-12 hours.

We utilize two sources of drug tests in this study. The first source includes workrelated drug tests conducted on employers' behalf by Quest Diagnostics. The workplace drug tests are not administered to a random sample of workers. Although some of the tests are random, another portion of the tests are conducted for particular reasons such as pre-employment screens, accidents, or "for cause". Tests that are done "for cause" are more likely to return a positive finding than tests conducted for other reasons. Not all employers test their employees. About 20 percent of employee drug tests in this series are from federally-mandated safety-sensitive workers while the remainder are from firms that have chosen to test their employees. The second source of drug tests are hospital records. These are tests of people admitted as inpatients to the hospital where either the patient reported drug use or the clinicians decided to test patients based on their symptoms. The downward bias that results from the fact that physicians choose to test only a subset of patients is likely to be modest as there is evidence that doctors do a good job of detecting drug use.²⁵ A more significant issue with measures generated from the hospital data is that people who experience an inpatient hospital stay are not representative of the general population.

To obtain a sense of how well these two measures of drug use capture variation in drug use, we compare them with each other given that the correlation between them is likely due to their correlation with underlying use rates. The correlation between the two series is 0.77, suggesting that they are both highly correlated with underlying drug use in the general population.

We also compare the estimates from the workplace and hospital testing with estimates of state-level prevalence from the National Survey on Drug Use and Health during the period from 2004 to 2007. We are restricted to making the comparison based on statelevel means calculated from a four year period because the survey will not support an analysis over a shorter period.

We present these comparisons in Figure 6. Each graph is a scatter plot of the average percent of drug tests that were positive against the average fraction of survey respondents reporting they used methamphetamine in the prior 12 months. The size of each bubble in the graphs is proportional to the square root of state population. The graphs reveal that

 $^{^{25}}$ In a randomized trial Schiller, Shumway and Batki (2000) find that in an urban psychiatric emergency room only eight percent of people that had used drugs recently did not have a drug test ordered for them by the doctor treating them. The bias is likely to be even larger for methamphetamine, as its use is more heavily stigmatized.

the drug tests are highly correlated with survey measures of methamphetamine use. The rates at which employees and hospital patients test positive for amphetamine are highly correlated with survey estimates of methamphetamine use in the general population with (population-weighted) correlations of 0.89 and 0.85, respectively.²⁶ The strength of these correlations suggest that these two drug testing measures are truly measuring underlying use. Despite the likely under-reporting in surveys, the percent of the population reporting use in the surveys is larger than the percent testing positive. This is likely due to the differing reference windows for the tests relative to the survey. The survey response is regarding the prior 12 months while the drug test will only pick up use in the prior 3-5 days.

We now turn to examining the impact of the OTC regulations on the rate at which individuals test positive for methamphetamine use in workplace drug tests. The workplace drug test data covers a shorter time period than our other datasets, with an endpoint of April 2006. Figure 7 shows that the share of employees that test positive for methamphetamine was slowly growing from 2002 through 2005. Figure 8 presents the results of the event study. While there is no obvious pre-trend in the conditional average positive test rate, there is also no clear change after the enactment of the OTC regulations. This is supported in each specification of our regressions, which are presented in Table 4. Each specification yielded a fairly precise estimate near zero. Column 2, which refers to the specification with the same controls as Figure 8, contains a point estimate of essentially zero. The standard error implies a 95 percent confidence interval with end-points that are less than ten percent of the average positive test rate prior to when the OTC restrictions were enacted. This is in stark contrast to the change observed for labs.

We also find no significant impact of the regulations on positive hospital toxicology test rates, though our estimates are less precise than they were for the workplace drug tests. Figure 9 shows the time series of the state average share of hospital admissions with a positive indication for amphetamine. Unlike our other outcomes, we do not have a full time series of admissions data for a few of the states, so we include a line in the figure that plots the percent of the population included in the sample at each point in time to indicate changes in sample composition. The average share of positive tests for methamphetamine at hospitals was generally increasing from January of 2002 through the end of 2005. The upwards trend broke sometime in the end of 2005 and by the end of 2007 the test rate was the same as it was at the beginning of 2002. Despite this pattern in

²⁶The state-specific estimates of methamphetamine use among the general population were generated by stacking four years of the National Survey on Drug Use and Health.

the time series of average positive test rates, the event study graph presented in Figure 10 reveals no impact of the regulations on positive test rates. This implies that most of the changes in the raw averages of Figure 9 were driven by common changes in the test rates across all states. Table 5 presents the regression results. None of the point estimates are significantly different from zero at conventional levels. We also present results for opioids, cocaine, and marijuana. There is no significant increase in the positive test rates for any of these other drugs.

5.3 Drug-Related Arrests

Even though the OTC restrictions did not significantly reduce our measures of methamphetamine consumption, the restrictions may have had an effect on drug-related arrests given their large impact on local methamphetamine production. If the reduction in the number of labs led to fewer people selling methamphetamine, then we may observe a decline in the arrest rate for drug sales. In this section, we examine the impact of the OTC restrictions on drug-related arrests. We find no evidence that the laws caused a change in arrest rates for the sale or possession of dangerous non-narcotics.

Figure 11 plots the average monthly arrest rates per 10,000 person years for sales and possession of dangerous non-narcotics, which includes methamphetamine, and addicting narcotics (eg heroin and other drugs with sleep-inducing properties). The arrest rate for possession of both types of drugs increased over the beginning of our sample window, but fell concurrently with the enactment of the laws.

The results of our regression estimates reveal that the reduction in arrests for possession in Figure 11 were driven by common changes across all states. Figure 12 presents the event study for drug-related arrests. The event study reveals no clear change in any of the arrest rates after the law. The regressions are presented in Table 6. None of our specifications provide evidence that the restrictions reduced the arrest rates for the sale or possession of non-narcotics, though some of the estimates are not very precisely estimated, which is not surprising given the volatility of the event study estimates for that outcome in Figure 12. Similarly, we find no evidence that the laws changed arrest rates for the sale or possession of narcotics. While a few of the specifications provided significant point estimates for the sale of addicting narcotics, the findings are not robust across specifications so we do not view this as persuasive evidence that the restrictions caused a change in drug-related arrest rates.

5.4 Robustness

Our identification strategy is uniquely strong relative to much of the drug literature in that it relies on variation in the timing of state laws and exploits interventions with known timing and geography. Our results show the number of methamphetamine laboratories in a state fell after the laws were enacted. But, despite the large reduction in the number of labs, there is no evidence that the laws led to a reduction in methamphetamine purity, consumption or arrests. Our review of DEA reports suggests a likely explanation: that within state production of methamphetamine comprises only part of the supply and out of state supply responded rapidly.

One might be concerned, however, that state laws may have been anticipated by larger retailers particularly for states that adopted later. In fact, newspaper reports document that several large pharmacy, supermarket and warehouse chains planned to implement the regulations nationwide around August 2005 even though the regulations had only been enacted in a limited number of states at the time ²⁷ If these plans were carried out, then any information leveraged from late adopting states would bias our estimates downward, which theoretically could contribute to the null findings. We believe this is a less likely explanation for our results than an increase in out of state supply because late adopters were less likely to have substantial methamphetamine problems. Nevertheless, we consider alternative specifications that focus more on the early adopters to provide further support for our conclusions.

Fortunately, 22 states enacted their laws before August 2005, the date several retailers planned to enact the law according to newspaper accounts. We explored the possibility that our main specification underestimates the effect of the law due to early retailer compliance by estimating three different specifications that focus on these 22 states. First, we estimated our base model using data only on states that enacted a law prior to August of 2005. Second, we estimated our base model for all states and included two separate post law indicator variables for states that enacted the law prior to August of 2005 and states that enacted the law after that date. Finally, we estimated our base model that includes a single treatment effect on data from all states but only on data up to August of 2005. We include only the results from the first specification in Appendix three, as each of the

²⁷Large retailers who planned on voluntarily imposing restrictions nationwide in July and August of 2005 include: Albertsons/Savon, CVS, Longs Drugs, Kmart, Rite Aid, Target, Walgreens and Walmart: $http: //www.signonsandiego.com/uniontrib/20050507/news_1b7pseudo.html$ (Last accessed January 6, 2013) and Sam's Club:

 $http: //www.msnbc.msn.com/id/7633871/ns/health - cold_and_flu/t/wal - mart - restrict - sales - cold - medicines/ (Last accessed January 6, 2013).$

three specifications gave qualitatively similar findings. Specifically, states that enacted a law early in the sample experienced large reductions in the number of laboratories, but no significant change in purity, consumption or arrests for the sale or possession of dangerous non-narcotics. The null findings for models which attempt to isolate the effects among early adopters lends further support for the hypothesis that the intervention impacted too small a share of methamphetamine supply and/or other producers were able to fulfill existing demand.

6 Interpretation and Conclusion

The effectiveness of supply-side enforcement efforts to disrupt drug markets and reduce consumption has been widely-debated (Grossman, Chaloupka and Shim 2002). The difficulties in estimating the effects of enforcement efforts are widely acknowledged and have compelled researchers to turn to quasi-experimental methods to address some of the limitations of previous research. Legislation to combat the recent methamphetamine expansion provides several natural experiments that can help us understand the benefits of supply-side controls. Still, these efforts have largely relied on time-series variation resulting from federal interventions.

The OTC regulations examined in this paper are the latest in a series of precursor regulations, but variation in the timing of implementation across states provides a unique and important opportunity to estimate the impact of reducing drug use and its harms. In this paper, we link changes in each state's regulatory environment with changes in the production of methamphetamine. The OTC laws successfully disrupted local methamphetamine production with the number of labs in the state declining by 36%. We estimate reductions in laboratories of all sizes, but the largest and most significant reductions were among the smaller laboratories. The laboratory series fails to show signs of recovery during the first year after the laws were enacted. Reductions in domestic production of methamphetamine represent a gain to society because the process of manufacturing methamphetamine imposes significant harms on the environment.

Despite the large reduction in the production of methamphetamine within a state, we find no evidence of reductions in methamphetamine purity, consumption, or arrests. One potential explanation consistent with our results is that small labs comprise a minority of methamphetmaine supply and that production may have shifted outside the U.S. This is consistent with DEA evidence that production capacity migrated around the time the state laws were enacted. While it is difficult to precisely estimate the share of methamphetamine that comes from abroad, one study estimates that the share of methamphetamine produced in large labs that are primarily found in Mexico decreased from 80% to 65% just before the state laws were implemented but then reverted back to 80% afterwards.²⁸ Relatedly, the amount of methamphetamine seized at the Southwest border of the United States and the number of laboratories seized in Mexico also increased from 2004 to 2006 by 19 and 35 percent, respectively.²⁹

Using rich administrative data and quasi-experimental methods that leverage variation in the timing of adoption across states, our analysis suggests that supply-side interventions effectively reduced the number of domestic methamphetamine laboratories. This reduction may have implications for public welfare given the costs associated with domestic production (e.g. toxic byproduct). However, we find no evidence that methamphetamine consumption declined, which may indicate that the laws impacted only a small share of supply and/or resulted in an increase in imported methamphetamine. The lack of success in reducing methamphetamine consumption and its harms is disappointing, especially given the likely costs associated with these laws. Unlike other federal precursor regulations, the OTC laws placed a burden on legitimate retailers and consumers of cold medicines, which has yet to be fully characterized. We look forward to estimating the cost of the regulations on legitimate consumers, producers, and retailers of cold medicines in future work.

²⁸These estimates were taken from the interim report of the Synthetic Drugs Interagency Working Group: https : $//www.ncjrs.gov/ondcppubs/publications/pdf/interim_rpt.pdf$, last accessed 12/31/2012.

 $^{^{29}}$ These estimates were taken from the Department of Justice's National Drug Intelligence Center National Drug Threat Assessment of 2010, available at *http*: //www.justice.gov/archive/ndic/pubs38/38661/38661p.pdf, last accessed 1/2/2013.

References

- **CRS**, "Methamphetamine: Background, Prevalence, and Federal Drug Control Policies," Technical Report, Congressional Research Service (CRS) 2007.
- Cunningham, James K. and Lon-Mu Liu, "Impacts of federal ephedrine and pseudoephedrine regulations on methamphetamine-related hospital admissions," Addiction, 2003, 98 (9), 1229–1237.
- Cunningham, Scott and Keith Finlay, "Parental Substance Use and Foster Care: Evidence from Two Methamphetamine Shocks," *Economic Inquiry*, 2013, 51 (1), 764–782.
- **DiNardo, John**, "Law enforcement, the price of cocaine and cocaine use," *Mathematical* and Computer Modelling, 1993, 17 (2), 53–64.
- **Dobkin, Carlos and Nancy Nicosia**, "The war on drugs: methamphetamine, public health, and crime," *The American Economic Review*, 2009, *99* (1), 324.
- Grossman, M., F. Chaloupka, and K. Shim, "Illegal Drug Use and Public Policy," *Health Affairs*, March 2002, 21 (2), 134–145.
- Horowitz, Joel L., "Should the DEA's STRIDE data be used for economic analyses of markets for illegal drugs?," *Journal of the American Statistical Association*, 2001, 96 (456), 1254–1271.
- Jacob, B., L. Lefgren, and E. Moretti, "The Dynamics of Criminal Behavior: Evidence from Weather Shocks," *Journal of Human Resources*, 2007, 42 (3).
- Kelly, Elaine and Imran Rasul, "Policing Cannabis and Drug Related Hospital Admissions: Evidence from Administrative Records," Technical Report, University College London Working Paper October 2012.
- Lynch, M., R. Kemp, L. Krenske, A. Conroy, and J. Webster, Patterns of Amphetamine Use: Initial Findings From the Amphetamines in Queensland Research Project, 2003, Brisbane: Crime and Misconduct Commission, 2003.
- McBride, D., Y. Terry-McElrath, J. Chriqui, J. O'Connor, J. VanderWaal, and K. Mattson, "State Methamphetamine Precursor Policies and Changes in Small Toxic Lab Methamphetamine Production," *The Journal of Drug Issues*, 2011, 41 (2), 253–282.

- Miron, Jeffrey, "The Effect of Drug Prohibition on Drug Prices: Evidence from the Markets for Cocaine and Heroin," *Review of Economics and Statistics*, 2003, 85 (3), 522–30.
- **NIDA**, "Methamphetamine Abuse and Addiction," Technical Report, National Institute on Drug Ause 2002.
- **ONDCP**, "The Economic Costs of Drug Abuse in the United States, 1999-2002," Technical Report, Office of National Drug Control Policy 2004.
- _____, "Interim Report from the Interagency Working Group on Synthetic Drugs to the Director of National Drug Control Policy," Technical Report, Office of National Drug Control Policy May 2005.
- _____, "Pushing Back Against Meth: A Progress Report on the Fight Against Methamphetamine in the United States," Technical Report, Office of National Drug Control Policy 2006.
- _____, "National Drug Control Budget: FY 2011 Funding Highlights," Technical Report, Office of National Drug Control Policy February 2010.
- Raphael, Steven and Rudolf Winter-Ember, "Identifying the Effect of Unemployment on Crime," *Journal of Law and Economics*, April 2001, 44 (1), 259–83.
- Rawson, R.A., A. Huber, P. Brethen, J. Obert, V. Gulati, S. Shoptaw, and
 W. Ling, "Status of methamphetamine users 2–5 years after outpatient treatment," Journal of Addictive Diseases, 2001, 21 (1), 107–119.
- SAMHSA, "The DASIS Report: Primary Methamphetamine/Amphetamine Admissions to Substance Abuse Treatment: 2005," Technical Report, Substance Abuse and Mental Health Services Administration (SAMHSA, Office of Applied Statistics) 2008.
- Schiller, Mark, Martha Shumway, and Steven Batki, "Utility of Routine Drug Screening in a Psychiatric Emergency Setting," *Psychiatric Services*, April 2000, 51 (4), 474–478.
- Simon, S.L., C.P. Domier, T. Sim, K. Richardson, R.A. Rawson, and W. Ling, "Cognitive performance of current methamphetamine and cocaine abusers," *Journal* of Addictive Diseases, 2001, 21 (1), 61–74.

- Stockwell, T., J. Zhao, T. Chikritzhs, and T. Greenfield, "What did you drink yesterday? Public health relevance of a recent recall method used in the 2004 Australian National Drug Strategy Household Survey," *Addiction*, June 2008, 103 (6), 919–928.
- Weatherburn, D., C. Jones, K. Freeman, and T. Makkai, "Supply control and harm reduction: lessons from the Australian heroin drought," *Addiction*, 2002, 98 (1), 83–91.
- Yuan, Yuehong and Jonathan P. Caulkins, "The effect of variation in high-level domestic drug enforcement on variation in drug prices," *Socio-Economic Planning Sciences*, 1998, 32 (4), 265–276.





Notes: Population weights are derived from the census. The size of the limit on daily purchases varies from state to state, but in most state laws it is 3.6 grams per day and 9 grams per 30 day period. In a few states the 30 day limit is 7.5 grams.

26



Figure 2: Methamphetamine Labs Discovered or Seized by Capacity

Notes: The time series above are constructed using records from the National Clandestine Laboratory Seizure System. The figure contains the average number of labs discovered in a state by month.



Figure 3: Event Study: Methamphetamine Labs Discovered or Seized by Capacity

Notes: Count of labs discovered was regressed on state fixed effects, year/month fixed effects, linear state time trends, and indicators corresponding to the number of months since any over the counter restriction went into effect. The graph contains OLS estimates of the coefficients on the indicators corresponding to the number of months since any over the counter restriction went into effect. The coefficient on the event dummy equal to one if a state enacted any OTC restriction in the next month was normalized to zero. The estimates include records for all 50 states and the District of Columbia from January 2002 through March 2008. Standard errors clustered by state are in parentheses.

 $\frac{28}{28}$



Figure 4: Price and Purity of Methamphetamine from STRIDE

Notes: Price is measured in dollars and purity is measured in percent. The time series contains averages of the average price per gram and purity of drugs purchased by the police in a state by month.

29



Figure 5: Event Study: Price and Purity of Methamphetamine from STRIDE

Notes: Price is measured in dollars and purity is measured in percent. Average Price and Average Purity were regressed on state fixed effects, year/month fixed effects, linear state time trends, and indicators corresponding to the number of months since any over the counter restriction went into effect. The regressions were weighted by the number of illegal drug transactions used to derive the average price and purity measures in a state/month. The graph contains OLS estimates of the coefficients on the indicators corresponding to the number of months since any over the counter restriction went into effect. The coefficient on the event dummy equal to one if a state passed an over counter restriction in the next month was normalized to zero. The estimates include records from the District of Columbia and all 50 states except for Nebraska for January 2002 through March 2008. In many smaller states there are months without any purchases. Standard errors clustered by state are in parentheses.

30



Figure 6: Correlations of Measures of Methamphetamine Use

Notes: The figures are scatter plots of the average percent of drug tests that are positive against the average percent of survey respondents in the National Survey on Drug Use and Health that report using methamphetamine in the past 12 months. The averages are calculated during the period from 2004 to 2007. Each bubble represents a state and the size of each bubble is proportional to state population.

 $\frac{3}{1}$



Figure 7: Percent of Workplace Drug Tests that are Positive for Amphetamines

Notes: The time series contains the average percent of positive workplace drug tests in a state by month. The data used to construct the time series above are extracted from the Office of National Drug Control Policy report "Pushing Back Against Meth". It was downloaded on February 2, 2007 from www.whitehousedrugpolicy.gov/publications/pdf/pushingback_against_meth.pdf. The time series is weighted by state population. The unweighted time series has a similar shape but is more variable. Standard errors clustered by state are in parentheses.

32



Figure 8: Event Study: Percent of Workplace Drug Tests that are Positive for Amphetamines

Notes: Percent of positive tests was regressed on state dummies, year/month fixed effects, state time trends, and indicators corresponding to the number of months since any over the counter restriction went into effect. The regressions were weighted by state population. The graph contains OLS estimates of the coefficients on the indicators corresponding to the number of months since any over the counter restriction went into effect. The coefficient on the event dummy equal to one if a state passed an over counter restriction in the next month was normalized to zero. The data used to construct the graph above are extracted from the Office of National Drug Control Policy report "Pushing Back Against Meth". It was downloaded on February 2, 2007 from www.whitehousedrugpolicy.gov/publications/pdf/pushingback_against_meth.pdf. The estimates include records from the District of Columbia and all 50 states for January 2002 through April 2006. Standard errors clustered by state are in parentheses.



Figure 9: Percent of Hospital Admissions with Positive Drug Test for Amphetamine (Ages 15-40)

Notes: This series is derived from the HCUP NIS which includes a 20 percent sample of community hospitals from the following states AR, CA, CO, CT, GA, HI, IL, IN, KS, KY, MA, MD, MI, MN, MO, NC, NE, NH, NV, NY, OH, OR, SC, TN, TX, UT, VT, WI, WV and 100 percent of the community hospitals from AZ, NJ, and WA. For Iowa it is a 20 percent sample before 2004 and all community hospitals from 2004-2007. Approximately 90 percent of hospital stays occur at community hospitals.

34



Figure 10: Event Study: Percent of Hospital Admissions with Positive Drug Test for Amphetamine (Ages 15-40)

 $\widetilde{c}_{\widetilde{U}}$

Notes: Percent of hospitalizations among 15-40 year olds that test positive for amphetamines was regressed on state fixed effects, year/month fixed effects, state time trends, and indicators corresponding to the number of months since any over the counter restriction went into effect. Regressions were weighted by state population between the ages of 15 and 40. The graph contains OLS estimates of the coefficients on the indicators corresponding to the number of months since any over the counter restriction went into effect. The coefficient on the dummy variable equal to one if a state passed an over counter restriction in the next month was normalized to zero. This series is derived from the HCUP NIS which includes a 20 percent sample of community hospitals from the following states AR, CA, CO, CT, GA, HI, IL, IN, KS, KY, MA, MD, MI, MN, MO, NC, NE, NH, NV, NY, OH, OR, SC, TN, TX, UT, VT, WI, WV and 100 percent of the community hospitals from AZ, NJ, and WA. For Iowa it is a 20 percent sample before 2004 and all community hospitals from 2004-2007. Approximately 90 percent of hospital stays occur at community hospitals. The estimates include records for January 2002 through December 2007. Standard errors clustered by state are in parentheses.



Figure 11: Drug Related Arrest Rate from Uniform Crime Reports

Notes: The series above are derived from the Uniform Crime Reports for January 2002 through December 2007. There is no data available for Alabama, Florida, and Rhode Island. Records from agencies in some states that report either annually or biannually have been dropped.

36



Figure 12: Event Study: Drug Related Arrest Rate from Uniform Crime Reports

Notes: Drug related arrest rates in a month per 10,000 people were regressed on state fixed effects, calendar time effects, state time trends, and indicators corresponding to the number of months since any over the counter restriction went into effect. The regression was weighted by state population. The graph contains OLS estimates of the coefficients on the indicators corresponding to the number of months since any over the counter restriction went into effect. The coefficient on the dummy variable equal to one if a state passed an over counter restriction in the next month was normalized to zero. The series above are derived from the Uniform Crime Reports for January 2002 through December 2007. There is no data available for Alabama, Florida, and Rhode Island. Records from agencies in some states that report either annually or biannually have been dropped. Standard errors clustered by state are in parentheses.

 $\frac{3}{7}$

		States				
	Limit on Amount	ID Required	Log Maintained	Stored Behind Counter	Any Restriction	Adopting Before Federal Law
Limit on Amount an Individual Can Purchase	1					35
ID Required at Time of Purchase	0.90	1				30
Log Maintained of Purchaser's Identity	0.88	0.97	1			24
Stored Behind Counter, in Line Of Sight or on Video	0.92	0.91	0.88	1		35
Any of the Restrictions Above	1.00	0.90	0.87	0.92	1	35

Table 1: State Laws Regulating the Sales of Over the Counter Medicines Containing Ephedrine or Pseudoephedrine

Notes: The correlations are all estimated weighted for state populations on data from January of 2004 through March of 2008. Only two states of the 35 states that implemented product placement restrictions (Louisiana and Michigan) allowed the items to be monitored by video or placed in a clerk's line of sight rather than behind a counter or in a locked counter.

		Num	ber of		Lab Capacity			
	Labs Seized					<u>Under 2 Ounces</u>		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
OTC Restriction	-6.71	-5.05	-7.02	-7.30	-4.08	-3.05	-4.73	-4.92
	(1.52)	(1.44)	(1.87)	(1.93)	(0.90)	(0.89)	(1.31)	(1.36)
Mean Prior to OTC Restriction	13.94	13.94	13.94	14.46	9.59	9.59	9.59	9.93
Observations	3825	3825	3825	3675	3825	3825	3825	3675
Number of States	51	51	51	49	51	51	51	49

Table 2: Impact of OTC Regulations on Methamphetamine Lab Ser

		Lab Ca	apacity			Lab Capacity				
	2 to 8 Ounces			(9 Ounces or More					
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)		
OTC Restriction	-2.29	-1.76	-1.87	-1.94	-0.34	-0.24	-0.42	-0.44		
	(0.55)	(0.47)	(0.56)	(0.58)	(0.22)	(0.19)	(0.21)	(0.21)		
Mean Prior to OTC Restriction	3.25	3.25	3.25	3.38	1.10	1.10	1.10	1.15		
Observations	3825	3825	3825	3675	3825	3825	3825	3675		
Number of States	51	51	51	49	51	51	51	49		
Linear State Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes		
Quadratic State Trends	No	No	Yes	Yes	No	No	Yes	Yes		
Covariates	No	No	No	Yes	No	No	No	Yes		

Notes: All regressions include state fixed effects and year/month fixed effects. The dependent variable in the regressions is count of labs seized or discovered in a month in a particular state. These are derived from the National Clandestine Laboratory Seizure System. The estimates include records for all 50 states and the District of Columbia from January 2002 through March 2008 [(6*12+3)*51=3825]. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. In the fourth specification we drop 150 observations because weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

		Price pe	er Gram			Purity			
		Methamp	hetamine	è]	Methamp	hetamin	е	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	2.89	2.19	-1.83	-2.12	6.15	4.49	3.81	4.18	
	(2.94)	(2.93)	(3.54)	(3.57)	(2.58)	(2.55)	(2.24)	(2.26)	
Mean Prior to OTC Restriction	49.13	49.13	49.13	48.60	56.64	56.64	56.64	56.32	
Observations	2,074	$2,\!074$	$2,\!074$	$1,\!995$	2,074	2,074	2,074	1,995	
Number of States	49	49	49	47	49	49	49	47	
	Price per Gram Purity								
		Coc	aine			$\overline{\operatorname{Coc}}$	aine		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	1.43	1.46	2.18	2.08	0.023	0.020	0.14	0.082	
	(2.37)	(2.38)	(2.58)	(2.64)	(1.29)	(1.52)	(1.65)	(1.70)	
Mean Prior to OTC Restriction	40.66	40.66	40.66	61.26	40.64	40.64	40.64	61.30	
Observations	$2,\!449$	$2,\!449$	$2,\!449$	$2,\!423$	$2,\!449$	$2,\!449$	$2,\!449$	$2,\!423$	
Number of States	50	50	50	48	50	50	50	48	
Price per Gram Purity									
Crack						Cr	ack		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	-3.94	-3.19	-1.39	-1.52	0.19	0.19	-0.42	-0.50	
	(2.68)	(2.33)	(3.36)	(3.21)	(1.36)	(1.28)	(1.14)	(1.18)	
Mean Prior to OTC Restriction	62.69	62.69	62.69	62.68	63.55	63.55	63.55	63.19	
Observations	$2,\!381$	$2,\!381$	$2,\!381$	$2,\!342$	2,381	$2,\!381$	$2,\!381$	2,342	
Number of States	50	50	50	48	50	50	50	48	
		Price pe	er Gram			Pu	rity		
		Her	roin			Hei	roin		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	-6.41	-6.44	-4.95	-3.81	3.51	2.40	3.00	3.37	
	(12.2)	(11.5)	(11.1)	(11.2)	(2.65)	(2.61)	(3.05)	(3.02)	
Mean Prior to OTC Restriction	122.04	122.04	122.04	122.03	45.79	45.79	45.79	45.77	
Observations	$1,\!166$	$1,\!166$	$1,\!166$	$1,\!165$	1,166	$1,\!166$	$1,\!166$	1,165	
Number of States	44	44	44	43	44	44	44	43	
Linear State Time Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes	
Quadratic State Time Trends	No	No	Yes	Yes	No	No	Yes	Yes	
Covariates	No	No	No	Yes	No	No	No	Yes	

Table 3: Impact of OTC Regulations on Drug Price and Purity

Notes: All regressions include state fixed effects and year/month fixed effects. The dependent value in the regressions is average price and average purity over the month of drugs purchased by law enforcement. Price is measured in dollars and purity is measured in percent. These are derived from the National Clandestine Laboratory Seizure System. The estimates include records from the District of Columbia and all 50 states except for Nebraska for January 2002 through March 2008 [(6*12+3)*50=3750]. In many smaller states there are months without any purchases particularly for Heroin and Methamphetamine. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

	Percent of Tests Positive						
	(1)	(2)	(3)	(4)			
OTC Restriction	0.016	-0.0095	-0.0079	-0.0093			
	(0.016)	(0.018)	(0.017)	(0.017)			
Mean Prior to OTC Restriction	0.365	0.365	0.365	0.362			
Observations	$2,\!652$	$2,\!652$	$2,\!652$	2,548			
Number of States	51	51	51	49			
Linear State Time Trends	No	Yes	Yes	Yes			
Quadratic State Time Trends	No	No	Yes	Yes			
Covariates	No	No	No	Yes			

Table 4: Percent of Workplace Drug Tests Positive for Methamphetamine

Notes: All regressions include state fixed effects and year/month fixed effects and were weighted by state population. Standard errors are clustered at the state level. The data used to construct the dependent variable are extracted from the Office of National Drug Control Policy report "Pushing Back Against Meth". It was downloaded on February 2, 2007 from

www.whitehousedrugpolicy.gov/publications/pdf/pushingback_against_meth.pdf. The dependent variable is the percent of drug tests that are positive. The estimates include records from the District of Columbia and all 50 states for January 2002 through April 2006 [(4*12+4)*51=2652]. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

		Amphe		Opioids					
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	0.11	0.083	0.060	0.074	-0.014	-0.093	-0.077	-0.11	
	(0.093)	(0.091)	(0.057)	(0.055)	(0.15)	(0.13)	(0.12)	(0.15)	
Mean Prior to OTC Restriction	0.671	0.671	0.671	0.656	1.912	1.912	1.912	1.928	
Observations	2316	2316	2316	2244	2316	2316	2316	2244	
Number of States	33	33	33	32	33	33	33	32	
Cocaine						Marijuana			
	(1)	(2)	(3)	(4)	(1)	$\overline{(2)}$	(3)	(4)	
OTC Restriction	-0.33	-0.29	-0.18	-0.22	-0.035	0.0041	0.11	0.11	
	(0.20)	(0.19)	(0.16)	(0.18)	(0.13)	(0.12)	(0.13)	(0.14)	
Mean Prior to OTC Restriction	2.201	2.201	2.201	2.201	1.895	1.895	1.895	1.896	
Observations	2316	2316	2316	2244	2316	2316	2316	2244	
Number of States	33	33	33	32	33	33	33	32	
Linear State Time Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes	
Quadratic State Time Trends	No	Yes	Yes	Yes	No	No	Yes	Yes	
Covariates	No	No	No	Yes	No	No	No	Yes	

Table 5: Percent of Hopitalizations with a Positive Drug Test

Notes: All specifications include state fixed effects and year/month fixed effects. Regressions are weighted by population between the ages of 15 and 40. Standard errors are clustered by state. The dependent variable in the regressions is the percent of hospitalizations among 15 to 40 years olds in a month in a state that test positive for a particular drug. This dependent variable is derived from the HCUP NIS which includes a 20 percent sample of community hospitals from the following states AR, CA, CO, CT, GA, HI, IL, IN, KS, KY, MA, MD, MI, MN, MO, NC, NE, NH, NV, NY, OH, OK, OR, SC, TN, TX, UT, VT, WI, WV and 100 percent of the community hospitals from AZ, NJ and WA. For Iowa it is a 20 percent sample before 2004 and all community hospitals from 2004-2007. Approximately 90 percent of hospital visits occur at community hospitals. The hospital records do not distinguish positive tests from methamphetamine from positive tests from amphetamine. In this period over 90 percent of positive tests for either methamphetamine or amphetamine are due to methamphetamine. The estimates include records for January 2002 through December 2007. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Standard errors clustered by state are in parentheses.

		$\frac{\text{Sales of Addicting}}{\text{Narcotics}}$					Sales of Dangerous <u>non-Narcotics</u>		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	-0.059	-0.066	-0.14	-0.13	0.014	0.013	-0.059	-0.061	
	(0.057)	(0.046)	(0.045)	(0.049)	(0.087)	(0.088)	(0.060)	(0.062)	
Rate per 10,000	0.726	0.726	0.726	0.728	1.746	1.746	1.746	1.745	
Observations	$3,\!477$	$3,\!477$	$3,\!477$	3,327	$3,\!477$	$3,\!477$	$3,\!477$	$3,\!327$	
Number of States	47	47	47	45	47	47	47	45	

Table 6: Impact of OTC Regulations on Drug Related Arrests

	Possession of Addicting				Pos	Possession of Dangerous				
		Narcotics				non-Narcotics				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)		
OTC Restriction	0.13	0.13	-0.056	-0.048	-0.26	-0.31	-0.32	-0.27		
	(0.12)	(0.11)	(0.099)	(0.11)	(0.91)	(0.93)	(0.44)	(0.43)		
Rate per $10,000$	1.572	1.572	1.572	1.577	8.409	8.409	8.409	8.428		
Observations	$3,\!477$	$3,\!477$	$3,\!477$	3,327	$3,\!477$	$3,\!477$	$3,\!477$	3,327		
Number of States	47	47	47	45	47	47	47	45		
Linear State Time Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes		
Quadratic State Time Trends	No	No	Yes	Yes	No	No	Yes	Yes		
Covariates	No	No	No	Yes	No	No	No	Yes		

Notes: All regressions include state fixed effects and month dummies. Standard errors are clustered at the state level. The dependent value in the regressions is arrest rate in a month per 10,000 people in a state. Regressions are weighted by state population. These are derived from the Uniform Crime Reports for January 2002 through December 2007. There is no data available for Alabama, Florida, New York, and Rhode Island. Records from agencies in some states that report either annually or biannually have been dropped. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Standard errors clustered by state are in parentheses.

A Appendix

A.1 Impact of OTC Regulations on Lab Seizures: Effect on Log of Seized Labs and Poisson Models

Table 1: Impact of OTC Regulations on Methamphetamine Lab Seizures: Poisson Regressions

	Number of		Lab C	Capacity
	Labs	Seized	Under	2 Ounces
	(1)	(2)	(1)	(2)
OTC Restriction	-0.47	-0.43	-0.45	-0.41
	(0.13)	(0.074)	(0.11)	(0.069)
Mean Prior to OTC Restriction	13.94	13.94	9.59	9.59
Observations	3825	3825	3825	3825
Number of States	51	51	51	51
	Lab C	apacity	Lab C	Capacity
	$\frac{\text{Lab C}}{2 \text{ to } 8}$	apacity Ounces	Lab C <u>9 Ounce</u>	Capacity es or More
	$\frac{\text{Lab C}}{2 \text{ to 8}}$ (1)	apacity Ounces (2)	$\frac{\text{Lab C}}{9 \text{ Ounce}}$ (1)	Capacity es or More (2)
OTC Restriction	$\frac{\text{Lab C}}{2 \text{ to 8}}$ (1) -0.78	apacity Ounces (2) -0.63	$ \frac{\text{Lab C}}{9 \text{ Ounce}} (1) -0.27 $	Capacity es or More (2) -0.34
OTC Restriction	$ \begin{array}{r} Lab C \\ \underline{2 to 8} \\ (1) \\ -0.78 \\ (0.15) \end{array} $	apacity <u>Ounces</u> (2) -0.63 (0.11)	$ \begin{array}{r} $	$ \begin{array}{r} \underline{\text{Capacity}} \\ \underline{\text{cs or More}} \\ (2) \\ -0.34 \\ (0.28) \end{array} $
OTC Restriction Mean Prior to OTC Restriction	$ \begin{array}{r} Lab C \\ \underline{2 to 8} \\ (1) \\ -0.78 \\ (0.15) \\ 3.25 \end{array} $	apacity <u>Ounces</u> (2) -0.63 (0.11) 3.25		<u>Capacity</u> es or More (2) -0.34 (0.28) 1.10
OTC Restriction Mean Prior to OTC Restriction Observations	$ \begin{array}{r} Lab C \\ \underline{2 to 8} \\ (1) \\ -0.78 \\ (0.15) \\ 3.25 \\ 3825 \end{array} $	$ \begin{array}{r} $	$ \begin{array}{r} $	$ \begin{array}{r} $
OTC Restriction Mean Prior to OTC Restriction Observations Number of States	$ \begin{array}{r} Lab C \\ \underline{2 to 8} \\ (1) \\ -0.78 \\ (0.15) \\ 3.25 \\ 3825 \\ 51 \\ \end{array} $	apacity <u>Ounces</u> (2) -0.63 (0.11) 3.25 3825 51	$\begin{array}{r} {\rm Lab\ C}\\ \underline{9\ Ounce}\\ (1)\\ -0.27\\ (0.34)\\ 1.10\\ 3825\\ 51\end{array}$	Capacity es or More (2) -0.34 (0.28) 1.10 3825 51
OTC Restriction Mean Prior to OTC Restriction Observations Number of States	$ \begin{array}{r} Lab C \\ \underline{2 to 8} \\ (1) \\ -0.78 \\ (0.15) \\ 3.25 \\ 3825 \\ 51 \end{array} $	$ \begin{array}{r} \underline{\text{apacity}} \\ \hline \underline{\text{Ounces}} \\ (2) \\ -0.63 \\ (0.11) \\ 3.25 \\ 3825 \\ 51 \end{array} $	$ \begin{array}{r} $	$\begin{array}{r} \underline{\text{Capacity}} \\ \underline{\text{cs or More}} \\ (2) \\ -0.34 \\ (0.28) \\ 1.10 \\ 3825 \\ 51 \end{array}$

Notes: All regressions include state fixed effects and year/month fixed effects. The dependent variable in the regressions is count of labs seized or discovered in a month in a particular state. These are derived from the National Clandestine Laboratory Seizure System. The estimates include records for all 50 states and the District of Columbia from January 2002 through March 2008 [(6*12+3)*51=3825]. Standard errors clustered by state are in parentheses.

	<u>Number of</u> Labs Seized					Lab Capacity Under 2 Ounces			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
OTC Restriction	-0.34	-0.24	-0.31	-0.31	-0.27	-0.18	-0.27	-0.27	
	(0.072)	(0.071)	(0.065)	(0.063)	(0.066)	(0.065)	(0.064)	(0.063)	
Mean Prior to OTC Restriction	13.94	13.94	13.94	14.46	9.59	9.59	9.59	9.93	
Observations	3825	3825	3825	3675	3825	3825	3825	3675	
Number of States	51	51	51	49	51	51	51	49	

		/ 1 , 1 , 1 , 1 , 1 , 1	
Table 7. Impact of CTC	' Rogulations on Log	(⊥N/othemphotemin(Lab Solzurogl
1aDE 2, $IIIDaCUUUUUUU$	Incentations on Log	$1 \pm m_{\text{cumaturbuccature}}$; Lan neizuresi

	$\frac{\text{Lab Capacity}}{2 \text{ to 8 Ounces}}$				Lab Capacity					
					9 Ounces or More					
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)		
OTC Restriction	-0.43	-0.32	-0.31	-0.32	-0.15	-0.095	-0.10	-0.11		
	(0.064)	(0.055)	(0.066)	(0.067)	(0.056)	(0.057)	(0.051)	(0.051)		
Mean Prior to OTC Restriction	3.25	3.25	3.25	3.38	1.10	1.10	1.10	1.15		
Observations	3825	3825	3825	3675	3825	3825	3825	3675		
Number of States	51	51	51	49	51	51	51	49		
Linear State Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes		
Quadratic State Trends	No	No	Yes	Yes	No	No	Yes	Yes		
Covariates	No	No	No	Yes	No	No	No	Yes		

Notes: All regressions include state fixed effects and year/month fixed effects. The dependent variable in the regressions is $\log(1+\text{count of labs})$ seized or discovered in a month in a particular state). These are derived from the National Clandestine Laboratory Seizure System. The estimates include records for all 50 states and the District of Columbia from January 2002 through March 2008 [(6*12+3)*51=3825]. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. In the fourth specification we drop 150 observations because weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

A.2 Impact of OTC Regulations on Lab Seizures Estimated Separately for All Lab Sizes

	Lab Capacity	Lab Capacity	Lab Capacity
	Under 2 Ounces	$\frac{1}{2 \text{ to 9 Ounces}}$	9 to 32 Ounces
OTC Restriction	-3.05	-1.76	-0.14
	(0.89)	(0.47)	(0.14)
Mean Prior to OTC Restriction	9.59	3.25	0.62
Observations	3825	3825	3825
Number of States	51	51	51
	Lab Capacity	Lab Capacity	Lab Capacity
	2 to 10 lbs	10 to 20 lbs	20 lbs or Greater
OTC Restriction	-0.15	0.023	0.027
	(0.078)	(0.026)	(0.019)
Mean Prior to OTC Restriction	0.33	0.08	0.07
Observations	3825	3825	3825
Number of States	51	51	51

Table 1: Impact of OTC Regulations on Methamphetamine Lab Seizures

Notes: All regressions include state fixed effects, year/month fixed effects, linear and quadratic state specific trends. The dependent variable in the regressions is count of labs seized or discovered in a month in a particular state. These are derived from the National Clandestine Laboratory Seizure System. The estimates include records for all 50 states and the District of Columbia from January 2002 through March 2008 [(6*12+3)*51=3825]. Standard errors clustered by state are in parentheses.

A.3 Estimates for Early Adopting States

	<u>Number of</u> Labs Seized					Lab Capacity Under 2 Ounces				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)		
OTC Restriction	-10.5	-11.2	-11.9	-12.0	-7.59	-8.14	-8.54	-8.64		
	(2.86)	(3.37)	(3.11)	(3.12)	(1.81)	(2.10)	(2.26)	(2.25)		
Mean Prior to OTC Restriction	25.33	25.33	25.33	26.57	18.03	18.03	18.03	18.91		
Observations	$1,\!650$	$1,\!650$	$1,\!650$	$1,\!575$	$1,\!650$	$1,\!650$	$1,\!650$	1,575		
Number of States	22	22	22	21	22	22	22	21		

Table 1: 1	Impact of OTC	Regulations or	ı Metham	phetamine	Lab Seizur	es: Early	Adopters
						- /	

. .

	Lab Ca	apacity	Lab Capacity						
2 to 8 Ounces				(9 Ounces or More				
(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)		
-2.68	-2.84	-2.86	-2.88	-0.19	-0.26	-0.51	-0.51		
(0.83)	(0.91)	(0.93)	(0.95)	(0.55)	(0.61)	(0.43)	(0.42)		
5.85	5.85	5.85	6.14	1.44	1.44	1.44	1.52		
$1,\!650$	$1,\!650$	$1,\!650$	1,575	$1,\!650$	$1,\!650$	$1,\!650$	1,575		
22	22	22	21	22	22	22	21		
No	Yes	Yes	Yes	No	Yes	Yes	Yes		
No	No	Yes	Yes	No	No	Yes	Yes		
No	No	No	Yes	No	No	No	Yes		
	(1) -2.68 (0.83) 5.85 1,650 22 No No No	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccc} & Lab \ Capacity \\ \hline 2 \ to \ 8 \ Ounces \\ \hline 2 \ to \ 8 \ Ounces \\ \hline 2 \ to \ 8 \ Ounces \\ \hline 2 \ to \ 8 \ Ounces \\ \hline 2 \ to \ 8 \ Ounces \\ \hline 2 \ to \ 8 \ Ounces \\ \hline 2 \ to \ 8 \ Ounces \\ \hline -2.68 \ -2.84 \ -2.86 \\ \hline (0.83) \ (0.91) \ (0.93) \\ \hline 5.85 \ 5.85 \ 5.85 \\ \hline 5.85 \ 5.85 \\ \hline 1,650 \ 1,650 \ 1,650 \\ \hline 22 \ 22 \ 22 \\ \hline \\ No \ Yes \ Yes \\ No \ No \ Yes \ No \\ No \ No \ No \ No \\ \end{array}$	$\begin{array}{c cccc} & Lab Capacity \\ \hline 2 \ to \ 8 \ Ounces \\ \hline \\ \hline \\ 2 \ to \ 8 \ Ounces \\ \hline \\ $	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		

- - -

Notes: All regressions include state fixed effects and year/month fixed effects. The dependent variable in the regressions is count of labs seized or discovered in a month in a particular state. These are derived from the National Clandestine Laboratory Seizure System. The estimates include records for the 22 states that enacted a law prior to August 1, 2005 from January 2002 through March 2008 [(6*12+3)*22=1650]. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. In the fourth specification we drop 75 observations because weather data is missing for Hawaii. Standard errors clustered by state are in parentheses.

	Price per Gram				Purity				
	I	Methamp	hetamin	e	Methamphetamine				
	(1)	(2)	(3)	(4)	(1) –	(2)	(3)	(4)	
OTC Restriction	-6.04	-5.46	-9.34	-9.85	-0.29	-0.44	-0.75	-0.68	
	(6.99)	(7.17)	(9.19)	(9.29)	(3.66)	(3.69)	(3.55)	(3.51)	
Mean Prior to OTC Restriction	55.04	55.04	55.04	58.84	44.30	44.30	44.30	42.31	
Observations	$1,\!204$	1,204	1,204	$1,\!145$	1,204	$1,\!204$	$1,\!204$	$1,\!145$	
Number of States	22	22	22	21	22	22	22	21	
Linear State Time Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes	
Quadratic State Time Trends	No	No	Yes	Yes	No	No	Yes	Yes	
Covariates	No	No	No	Yes	No	No	No	Yes	

Table 2: Impact of OTC Regulations on Drug Price and Purity: Early Adopters

Notes: All regressions include state fixed effects and year/month fixed effects. Standard errors are clustered at the state level. The dependent value in the regressions is average price and average purity over the month of drugs purchased by law enforcement. Price is measured in dollars and purity is measured in percent. These are derived from the National Clandestine Laboratory Seizure System. The estimates include records for the 22 states that enacted a law prior to August 1, 2005 from January 2002 through March 2008 [(6*12+3)*22=1650]. In many smaller states there are months without any purchases particularly for Heroin and Methamphetamine. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

	Percent of Tests Positive					
	(1)	(2)	(3)	(4)		
OTC Restriction	-0.019	-0.032	-0.021	-0.018		
	(0.032)	(0.026)	(0.028)	(0.028)		
Mean Prior to OTC Restriction	0.434	0.434	0.434	0.424		
Observations	$1,\!672$	$1,\!672$	$1,\!672$	$1,\!596$		
Number of States	22	22	22	21		
Linear State Time Trends	No	\mathbf{V}_{0S}	\mathbf{V}_{OS}	$\mathbf{V}_{\mathbf{OS}}$		
Linear State Time Hends	NO	res	res	res		
Quadratic State Time Trends	No	No	Yes	Yes		
Covariates	No	No	No	Yes		

Table 3: Percent of Workplace Drug Tests Positive for Methamphetamine: Early Adopters

Notes: All regressions include state fixed effects and year/month fixed effects and were weighted by state population. Standard errors are clustered at the state level. The data used to construct the dependent variable are extracted from the Office of National Drug Control Policy report "Pushing Back Against Meth". It was downloaded on February 2, 2007 from

www.whitehousedrugpolicy.gov/publications/pdf/pushingback_against_meth.pdf. The dependent variable is the percent of drug tests that are positive. The estimates include records for the 22 states that enacted a law prior to August 1, 2005 from January 2002 through April 2008 [(6*12+4)*22=1672]. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

		Amphe		
	(1)	(2)	(3)	(4)
OTC Restriction	0.020	0.017	-0.098	-0.063
	(0.27)	(0.26)	(0.15)	(0.14)
Mean Prior to OTC Restriction	0.671	0.671	0.671	0.656
Observations	972	972	972	900
Number of States	14	14	14	14

Table 4: Percent of Hopitalizations with a Positive Drug Test: Early Adopters

Notes: All specifications include state fixed effects and year/month fixed effects. Regressions are weighted by population between the ages of 15 and 40. Standard errors are clustered by state. The dependent variable in the regressions is the percent of hospitalizations among 15 to 40 years olds in a month in a state that test positive for a particular drug. This dependent variable is derived from the HCUP NIS which includes a 20 percent sample of community hospitals from the following states that enacted a law prior to August 1, 2005: AR, CO, GA, IN, KS, KY, MN, OR, WV and 100 percent of the community hospitals from WA. For Iowa it is a 20 percent sample before 2004 and all community hospitals from 2004-2007. Approximately 90 percent of hospital visits occur at community hospitals. The hospital records do not distinguish positive tests from methamphetamine from positive tests from amphetamine are due to methamphetamine. The estimates include records for January 2002 through December 2007. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.

	Sale of Dangerous				Possession of Dangerous					
		Non-Na	arcotics		non-Narcotics					
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)		
OTC Restriction	-0.103	-0.114	-0.213	-0.230	0.615	0.630	0.00499	0.0516		
	(0.177)	(0.183)	(0.131)	(0.132)	(1.305)	(1.312)	(0.516)	(0.509)		
Rate per 10,000	2.04	2.04	2.04	2.03	5.92	5.92	5.92	5.87		
Observations	$1,\!488$	1,488	1,488	1,413	$1,\!488$	1,488	$1,\!488$	$1,\!413$		
Number of States	20	20	20	19	20	20	20	19		
Linear State Time Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes		
Quadratic State Time Trends	No	No	Yes	Yes	No	No	Yes	Yes		
Covariates	No	No	No	Yes	No	No	No	Yes		

Table 5: Impact of OTC Regulations on Drug Related Arrests: Early Adopters

Notes: All regressions include state fixed effects and month dummies. Standard errors are clustered at the state level. The dependent value in the regressions is arrest rate in a month per 10,000 people in a state. Regressions are weighted by state population. These are derived from the Uniform Crime Reports for January 2002 through December 2007. There is no data available for Alabama, Florida, and Rhode Island. Records from agencies in some states that report either annually or biannually have been dropped. Covariates include the unemployment rate, number of households receiving food stamps, average temperature and precipitation. Weather data is missing for Alaska and Hawaii. Standard errors clustered by state are in parentheses.