Breaking the Crystal Meth Economy: The Effects of Over the Counter Medicine Restrictions on Drug-Related Crime in the United States

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Job Market Paper
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Abstract

What is the impact of illegal drug use on crime? Research on this question has been hindered by the lack of a major exogenous 'lever' affecting drug consumption. I use the mid-2000's U.S. crackdown on the Over-the-Counter (OTC) sale of pseudoephedrine-based medications to investigate the effect of crystal methamphetamine on crime. The domestic and localized nature of crystal meth production, performed synthesizing pseudoephedrine, enabled OTC restrictions to disrupt the clandestine economy built around the drug. To guide the empirical exercise, I model the choices of a heavy meth consumer at the margins of crime. I combine a rational addiction framework à la Becker-Murphy (1988) with Becker's model of crime (1968). The positive price shock induced by the reform deters drug abuse, but discourages drug-motivated crime only for 'sufficiently' high prices. Several quasi-experimental designs, performed on a newly assembled DEA-FBI panel of U.S. counties, lend support to the model's predictions. Crime fell by approximately 10 percent in areas adopting the policy. OTC restrictions cut heavy drug abuse, reducing acquisitive crimes undertaken to sustain the habit (economic channel), and violent crimes committed under the influence of the drug (psychological channel). Crucially, the analysis allows to parse out violence associated with illegal drug trafficking (systemic channel), from violence committed 'under the influence'. A calculation based on the evidence of the paper, which consistently points to a 30-35 percent decline in meth usage, provides boundaries for the drug-crime elasticity in the range of 0.1 to 0.4.

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1 Introduction

Over the past four decades, the U.S. federal and state governments have poured over $1 trillion to finance drug enforcement policies (DPA, 2015). Despite this massive effort, the market for illegal drugs continues to expand, motivating the ongoing policy-debate that deeply questions the effectiveness of the 'War on Drugs' (UNODC, 2010; ODCPP, 2002). In the United States, the production, distribution and consumption of illegal substances generate an annual social cost of $200 billion, a figure that reflects lost productivity, environmental destruction, healthcare expenditures, and criminal activity (ONDCP, 2007). This paper focuses on the drug-crime nexus. Approximately 60 percent of U.S. inmates, corresponding to 1.2 million people, tested positive at the time of arrest for marijuana, cocaine, heroin, or methamphetamine (NACDD, 2014).

The propagation of illegal drug markets can exacerbate criminal activity via three major channels: 1) economic, related to users' need to support their drug-habits or to their inability to work, typically resulting in the proliferation of acquisitive crimes; 2) pharmacological, associated with the psychosis arising with the immediate or chronic effects of drug consumption, with implications for physical and sexual violence; and 3) systemic, connected with the production and trafficking of the drug itself, exemplified by gang violence to control territory (Goldstein, 1985).

Quantifying these channels, and establishing their relative importance, is crucial to devise cost-effective policies. However, assessing existence, empirical relevance, and direction of causality of these effects has proven difficult. Two main obstacles have hindered such analysis. First, illegal operations are inherently difficult to measure, mainly because of their covert nature. Second, criminal activity is endogenous to the proliferation of illegal drugs.

This paper focuses on crystal methamphetamine, an addictive synthetic stimulant commonly referred to as crystal meth. Besides its intrinsic policy relevance, the case of crystal meth offers a unique opportunity to quantify and distinguish among competing channels linking drug to crime.[1]

I examine over-the-counter (OTC) restrictions to the sale of ephedrine or pseudoephedrine. These are chemicals contained in common cold medicines that, prior to the introduction of the restrictions, could be easily obtained from pharmacies and local stores. Ephedrine or pseudoephedrine are critical inputs that can be used to synthesize crystal methamphetamine in clandestine, toxic home-labs.

The structure of the domestic retail market for methamphetamine creates a special window for modeling the OTC reforms as an exogenous 'lever' that dramatically disrupted production and consumption patterns. Unlike other drug markets (e.g., crack cocaine and heroin), this market is organized around a 'cottage industry' model: production is undertaken in small to medium sized meth labs, typically run by extreme addicts (Eck and Gersh, 2000; DEA, 2010). This feature made the economy around the drug highly vulnerable to the effects of the OTC reforms. The policies choked off access to a major intermediate input for crystal meth production, inducing sharp changes in drug prices and production levels.

In this paper, I argue that the implementation of the OTC reforms isolates plausibly exogenous variation in crystal meth exposure for a subpopulation of extreme, potentially dangerous users. This

[1] Law-enforcement agencies consider crystal meth to be one of the most dangerous drugs in the United States (NACO, 2005).

quasi-natural experiment represents one of best opportunities available for studying the causal link between drug use and criminal behavior, since the source of the drop in availability can be clearly pinned down.

I assembled a novel, county-level panel dataset. I merged Federal Bureau of Investigation (FBI) data on property crimes, violent crimes, drug-related arrests, and circumstances surrounding homicides (which differentiates between crimes of 'passion' and systemic violence), with detailed Drug Enforcement Agency (DEA) information on the location and number of clandestine meth-labs seized by police. I supplemented this further with national evidence on drug prices, purities, emergency hospitalizations, and drug testing; state-level data on admissions to substance abuse treatment facilities, and a wide set of county-level socio-economic controls. The final dataset contains annual information over a 10-year period (2001-2010) for 2,200 counties in all 50 states covering 94 percent of the U.S. population.

I propose a novel theoretical framework to guide the empirical analysis. The framework captures the salient aspects of heavy meth consumers: addiction, consumption and both an economic and pharmacological motive for crime. My model combines – in a novel stylized manner – a rational addiction framework à la Becker-Murphy (1988), with Becker's model of crime (1968). The agent reduces his losses when meth usage is closer to addiction: addicts desperately attempt to avoid withdrawal symptoms, but also potentially lethal overdosing. I model the introduction of the OTC reforms as an unexpected shock to crystal meth prices. This imposes an extra-cost on the habit, incentivizing criminal activity participation, which comes at a higher inherent cost. Two central findings emerge: i) an unexpected increase in drug prices, while deterring drug abuse, leads to non-linear effects on criminal behavior; ii) 'sufficiently' high prices discourage drug-related crime.

I use as a main empirical specification a difference-in-differences (DD) design. I compare changes in crime between counties in: i) states that implemented OTC regulations in 2005, and ii) states that did not adopt any OTC restrictions (before and after the implementation of other states' regulatory changes).[2] I detect a significant reduction of 5 percent to 10 percent in burglaries and larcenies. This captures the presence of an economic channel influencing criminal behavior. The effects are concentrated in the year of the implementation and in the year after. I find similar reductions on aggravated assaults and murders. An analysis of the circumstances surrounding homicides helps me to parse out the psychological from the systemic channel: both channels can lead to violent crime. I detect a drop of 8.2 percent in murders connected to brawls and violent altercations, supporting the hypothesis that the OTC reforms decreased violence motivated by the psychotic effects of the drug (McKetin et al., 2014).[3] Conversely, I do not observe any change in murders connected to the systemic violence hypothesis (such as drug laws offenses and gang related killings). This violence is typically associated with more professional drug markets (DEA, 2010). Finally, heterogeneity analysis shows that the crime reduction was greater in i) rural counties, ii) and areas with higher pre-existing concentrations of meth labs. These places are classified as hotbeds of crystal meth abuse

[2] I provide evidence of parallel trends in both property and violent crime, supporting the validity of the empirical approach.

[3] I also find significant signs of a decline in rape. Crystal meth is classified as a 'club' and a 'date-rape' drug, inducing sexual violence primary via psychological channels (FBI, 2010).

(DEA, 2010).

The evidence supports the hypothesis that the OTC reforms led to a sharp reduction in meth usage. Monitoring the Future, a nationally representative study of American young adults, shows that lifetime prevalence of crystal meth decreased by 30 percent from 2004 to 2005. Quest Diagnostics, the major provider of tests for illegal drugs in the United States, shows a national reduction among those undergoing workplace tests for crystal meth use of 15.2 percent (2004-2005) and 35.7 percent (2004-2006).[4] An analysis of the state-level Treatment Episode Data Set (TEDS) reveals a 34 percent increase in meth-related hospitalizations for detoxification, rehabilitation, and ambulatory care for withdrawal symptoms. No effect is detected for alcohol, crack cocaine, heroin, marijuana or LSD. A calculation based on the evidence of the paper, which consistently points to a 30-35 percent decline in use, provides boundaries for the crime-meth elasticity in the range of 0.1 to 0.4.[5]

This paper contributes to several strands of the literature. First, it provides compelling evidence on the effects of drug usage on crime. Previous work in this area has employed time-series and panel data techniques (Corman and Mocan, 2000; Grogger and Willis, 2000; Fryer et al. 2013). I use the introduction of the OTC reforms to isolate plausibly exogenous variation in crystal meth exposure for a subpopulation of extreme, potentially dangerous users.[6] To the extent of my knowledge, this is also the first study that provides separate estimates for the economic, the psychological and the systemic channel discussed above.

My study is connected to a recent literature that focuses on how drug policy interventions affect criminal activity. Dell (2014) uses a regression discontinuity design to show that drug-related violence substantially increases after close elections of National Action Party (PAN) mayors in Mexico. Her findings suggest that this violence is caused by rival traffickers' attempts to usurp territories after police crackdowns weakened incumbent criminals. Adda, McConnel and Rasul (2014) show that a cannabis de-penalization policy in the London borough of Lambeth caused police to re-allocate effort toward non-drug-related crime, leading to a reduction of all these felonies.[7]

Finally, my work complements two papers on methamphetamine market. Dobkin, Nicosia and Weinberg (2014) find that the implementation of the OTC reforms decreased by 36 percent the number of active meth-labs in the United States. I extend their analysis investigating the impact on crime, aiming also at identifying the underlying operating channels.[8] Dobkin and Nicosia (2009) estimate the effects of a different government program targeting the supply of crystal meth in

[4]The drop in consumption is supported by ethnographies describing the impact of these restrictions on the behavior of extreme meth addicts (Sexton et al. 2008, Lopez, 2014).

[5]Other potential mechanisms such as: the relocation of crime across borders, spillovers on the demand or supply of other illicit substances, and possible changes in policing activities following the reforms are discussed in the online appendixes. No significant effects are detected.

[6]In using quasi-experimental designs this paper belongs to a recent literature in the economics of crime. See Aizer and Doyle (2013); d'Este (2015); Draca Koutmeridis and Machin (2015); Mastrobuoni and Pinotti (2015).

[7]See also: Angrist and Kugler (2008), Meija et al. (2014), Rozo (2014), Dube and Naidu (2015).

[8]Dobkin, Nicosia, and Weinberg (2014) estimate that these effects are driven by the exit of small to medium capacity labs, leading to a decrease in U.S. 'domestic' production of 25%. They do not detect any change in methamphetamine consumption, suggesting that Mexican production filled the void in the U.S. drug market. My overall analysis supports the hypothesis that a subpopulation of extreme dangerous users reduced meth consumption after the implementation of the reforms.

1995. No effects are detected for property and violent crime in California. My work broadens this geographical horizon, assembling a novel county level DEA-FBI dataset, covering almost the entire U.S. landscape.

This paper unfolds as follows: section II provides the institutional background; section III presents the theoretical framework; section IV presents the data sources and the main empirical design; section V reports related-results, robustness checks and placebo exercises; section V explores the mechanisms; section VI concludes and discusses various policy implications.[9]

2 Institutional Background

This section provides a comprehensive institutional background on the incidence of crystal methamphetamine usage in the United States. I first examine personal effects on users, emphasizing the links with criminal behavior. Then, I focus on the main features of the domestic market. Finally, I report the details of states and federal legislation limiting the access to meth chemical precursors.

2.1 Methamphetamine's Effects

Methamphetamine is a powerful, highly addictive stimulant that affects the central nervous system. Also known as meth, chalk, ice, and crystal, it costs between $20 and $25 for 0.25 grams.[10] The drug takes the form of a white, odorless, bitter-tasting crystalline powder that easily dissolves in water or alcohol. Methamphetamine can be smoked, snorted, injected, or ingested to produce a release of high levels of dopamine and neurotransmitters into the brain. This generates sensations of self-confidence, energy, alertness, pleasure, and sexual arousal.

With repeated use, meth exhausts accumulations of dopamine in the brain, and simultaneously destroys the wiring of dopamine receptors. This process makes crystal meth addictive. Users continually "chase" the high that the drug provided initially, and because they seek to counteract the lows they feel subsequently when they are not using the drug.

Chronic abuse can lead to psychotic behavior, hallucinations, paranoia, violent rages, mood disturbances, insomnia, psychosis, poor coping abilities, sexual dysfunction, dermatological conditions and "meth mouth". This is a dental condition characterized by severe decay and loss of teeth, fracture and enamel erosion (NIDA, 2002). The termination of use can result in depression, fatigue, anxiety, agitation, vivid or lucid dreams, suicidal temptation, psychosis resembling schizophrenia and paranoia (ONDCP 2003).[11]

[9] Online appendix Ashows supplementary tables and figures, presents the analysis of drugs related arrests and of geographical spillovers; online appendix B presents an instrumental variable approach, designed to address the endogenous entry (or opening) of meth labs, and to capture its effects on the propagation of criminal activity. Online appendix B also presents: i) a DD design exploiting a subsequent federal act, mainly implemented to avoid potential reallocations of meth production in states who did not implement the laws; ii) the examination of the long-run effects of OTC restrictions; and iii) a case study on U.S. states close to Mexico, the main provider of methamphetamines to the United States via Mexican cartels.

[10] More information can be found at: http://www.crystalmethaddiction.org/.

[11] Unlike many other illegal drugs, methamphetamine is a drug that appeals equally to men and women. All of

2.2 Methamphetamine-Related Criminal Activity: Supportive Evidence

Crystal methamphetamine enormously raises the energy level of a meth addict who is under its influence; conversely, addicts going through withdrawal often experience fatigue, sleep excessively and exhibit suicidal tendencies. While a significant proportion of methamphetamine-related property crimes can be attributed to users' need to fund their drug purchases:

> "... Many property and violent crimes are more likely a result of the pharmacological stimulant effects of this substance, which is at its peak when the extreme meth-user is under the influence " (DEA, 2013).[12]

McKetin et al. (2014) administered a structured interview on a sample 238 individuals, characterized by different levels of meth consumption and addiction.[13] The findings highlight a clear dose–response increase in violent behavior. This effect was especially large for frequent methamphetamine use (i.e. 16+ days of use in the past month). This increased the odds of violent behavior tenfold, threefold with less frequent use. These results indicate that the probability of violent behavior increases from 10 percent during periods of abstinence to 60 percent during periods of heavy abuse.[14]

The National Association of Counties (NACO) administers an annual telephone survey to law enforcement agencies to investigate the impact of various illegal drugs on the proliferation of criminal activity. In 2005, when law enforcement officials from 500 counties in 45 U.S. states were asked to select the illegal drug that was the biggest problem in their county, crystal methamphetamine ranked first among 58 percent of the counties that took part in the survey; the results reflect the crystal meth's pervasive role in thefts, property crimes, physical and sexual violence.[15]

Arrestee Drug Abuse Monitoring Data (ADAM) provides further insights by recording the prevalence of methamphetamine use among the adult male population arrested for property and violent crimes. In 2003 (the last year these data were published before the implementation of OTC restrictions), the national mean of this group who tested positive for methamphetamine was 4.7 percent. The national mean of arrestees who reported the use of methamphetamine within the previous year in 2003 was 7.7 percent. These figures hide a great deal of variation across geographical locations.

the national data sets show an almost equal gender split for self reported meth use. Users also tend to be white and in their 20s and 30s. Though both cocaine and methamphetamine are stimulants, a comparison of characteristics of methamphetamine users and cocaine or crack users indicates that the two drugs do not, for the most part, share a common user group; that is, the drugs do not seem to substitute for each other or appeal to the same users (Hunt et al., 2006).

[12] To give a simple sense of the power of this illegal drug, while the high from cocaine can last from 30 minutes to one hour, the rush from methamphetamine lasts from eight to 24 hours. More information can be found at: http://www.drugabuse.gov

[13] Recruitment of the cohort took place in 2006 and 2007, while follow-up interviews spanned the period from 2006 to 2010.

[14] Several medical evidence related to methamphetamine and criminal behavior exist. See also Cartier et al. (2006), Dark et al. (2010), Sommers and Baskin (2006).

[15] Methamphetamine was followed in the ranking by cocaine (19 percent), marijuana (17 percent) and heroin (3 percent). The U.S. government reports that in 2008, 13 million people over the age of 12 have used methamphetamine, and 529,000 of those were regular users. More information is available at: http://www.drugfreeworld.org/drugfacts/crystalmeth/a-worldwide-epidemic-of-addiction.html

As an example, ADAM program data indicate that 12 percent of adult male arrestees in Seattle tested positive for the presence of methamphetamine in 2003, while 32.1 percent tested positive in Spokane, 45 percent in Sacramento, 28 percent in Portland Oregon, and 44 percent in San Diego (ADAM, 2003).[16]

2.3 The Domestic Market for Methamphetamine

Imported illegal drugs such as cocaine or heroin have hierarchical and complex distributional systems. These substances originate from agricultural products that need to be harvested, processed at several junctures, shipped, and eventually packaged for different levels of distribution. These steps involve growers, extractors, producers, transporters, smugglers, distributors and numerous other people who are needed to move the illegal product across borders.

Unlike heroin, or powdered or crack cocaine, methamphetamine is an entirely synthetic product that can be easily and inexpensively manufactured with little equipment, few supplies, and almost no expertise in chemistry. For this reason, the meth "cook" – particularly in the case of smaller labs – is often a heavy meth user turned producer, accepting the risk of a harsher criminal sentence in order to sustain his or her drug habit. The domestic market for crystal meth is particularly segmented. Methamphetamine produced in small and medium-sized "mom and pop" labs is typically sold to a close network of family and acquaintances – usually sharing comparable levels of addiction – rather than to strangers in the streets.[17]

Ephedrine or pseudoephedrine is the essential ingredient in the synthesis of crystal methamphetamine. This chemical is contained in medicines that help relieve the symptoms of a common cold or flu. If not in pure powder, this chemical needs to be separated from the tablets of cold medicine that contain it. For this purpose, cold tablets are mixed with sodium hydroxide, anhydrous ammonia, iodine, matches containing red phosphorus, Drano (a drain cleaner product), ether, brake and lighter fluid, and hydrochloric acid. These are all legal products that can be easily bought in local stores.

The entire chemical process is performed in self-made chemical labs hidden in apartments, caravans, garages or hotel rooms. The process generally takes about two days, and can result in hundreds of thousands of methamphetamine doses. These "mom and pop" labs can produce methamphetamine

[16] More than half of the 500 responding local law enforcement agencies reported that meth-related arrests accounted for up to 20 percent of arrests made in their counties during the last five years; another 17 percent of law enforcement agencies reported that meth-related arrests represented more than half of all their arrests.

[17] Ethnographic reports indicate that the methamphetamine retail market is different from other drug markets in many areas and reflects in large part what has been termed a "cottage industry" model of drug distribution (Eck and Gersh, 2000). In contrast to drug markets involving larger or more organized networks, the meth network is characterized by a large number of small groups; weak or little organizational structure; and fluid group membership. The segmentation of the markets for methamphetamine is supported by evidence from Arrestee Drug Abuse Monitoring (ADAM) Program, showing that crack users are involved with more different dealers than meth users. Moreover, meth distribution typically happens indoors rather than outdoors. In Sacramento, for example, arrestees report that on average they obtained meth from just over two dealers in the last 30 days; crack users report they obtained from, on average, over four dealers in the last 30 days (Hunt and Kuck, 2004). Many other cities (e.g. San Diego; Phoenix; Portland) have similar data.

easily and relatively cheaply. The DEA estimates that with about $100 of materials, a "cook" or meth manufacturer using the chemicals described above can produce about $1,000 worth of the product in few hours (DEA, 2003).[18]

2.4 OTC States and Federal Restrictions

In the last 25 years, the federal government has passed several laws intended to cut the diversion of ephedrine and pseudoephedrine to illegal drug labs.[19] This paper examines the effects of over-the-counter (OTC) restrictions implemented mainly in the year 2005. These policies were implemented as a reaction to a rapid increase in the number of toxic labs where the manufacturing of this substance occurred.

These policies exclusively regulated the access to the methamphetamine's precursor chemicals, ephedrine and pseudoephedrine, through: 1) quantity limitations, 2) sales environment restrictions, 3) proof of identification upon purchase, and 4) logbooks to prevent people from subverting the law by making repeated purchases.[20]

Policy activity restricting the access to methamphetamine's precursor chemicals has not been limited to the state level. Federal legislation took place in 2006 through the Combat Methamphetamine Epidemic Act (CMEA). The last provision of the federal act became effective September 30, 2006. This set a nationwide baseline standard for how to legally sell these products.[21]

Figure 1 shows a map of the United States highlighting the year in which any OTC restriction (either at the state or federal level) was implemented for the first time in each state.

[Figure 1]

Utah was the first to authorize a state regulation in 2001, followed by Oklahoma in 2004. The remaining states can be divided into three different groups:

1) Early Adopters, enacting a state law in the year 2005 are: Alabama, Arizona, Arkansas, California, Colorado, Delaware, Florida, Georgia, Hawaii, Indiana, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Jersey, New Mexico, North Dakota, Oregon, Tennessee, Texas, Virginia, Washington, West Virginia, Wisconsin, and Wyoming;

[18] The majority of methamphetamine distributed across the United States arrives via Mexican Cartels, or it is internally manufactured in "super-labs" capable of producing 10 pounds or more in a 24-hour period. This requires large-scale diversion of ephedrine/pseudoephedrine from legitimate industry by criminal organizations (DEA, 2006).

[19] See Dobkin, Nicosia and Weinberg (2014) for a detailed description.

[20] An accurate description including details about all states' regulations, date of approval and date of enactment can be found in the following report: "Pushing Back Against Meth: a Progress Report on the Fight Against Methamphetamines in the United States", Office of National Drug Control Policy (ONDCP), November 2006.

[21] The Combat Methamphetamine Epidemic Act of 2005 (CMEA) was signed into law on March 9, 2006, to regulate retail over-the-counter sales of ephedrine, pseudoephedrine, and phenylpropanolamine products. Retail provisions of the CMEA include daily sales limits and 30-day purchase limits, placement of product out of direct customer access, sales logbooks, customer ID verification, employee training, and self-certification of regulated sellers. Although the CMEA was effective nationwide, the State laws, which vary widely in content, were concurrently in effect. As a practical matter, the stricter provisions applied – whether contained in the state or federal law.

2) Late Adopters, authorizing a state law mainly at the beginning of 2006, are: Idaho, Illinois, North Carolina, Ohio, South Carolina, South Dakota, Alaska, Maine and Vermont;

3) CMEA Only adopters, where only the federal regulation became effective on September 30, 2006. These are: Connecticut, Maryland, Massachusetts, Nevada, New Hampshire, New York, Pennsylvania, and Rhode Island. The timing of the enactment of these laws gave rise to multiple experimental designs. These will be discussed in the rest of the paper and online appendices.

3 A Theoretical Framework

Prior to policy interventions, extreme users enjoyed a preferential access to crystal methamphetamines. This is because they produced the substance themselves or because they could acquire it from someone within their close network of acquaintances, sharing the same habit. State interventions dramatically augmented effective production costs, hitting – *de facto* – extreme users with a significant price shock.

From a theoretical perspective, the impact on crime is *ex-ante* ambiguous. On the one hand, these policies could have led to an upsurge of acquisitive crimes (as well as of violent crimes) committed by heavy users to compensate for the higher cost of addiction. On the other hand, heavy users might have been forced to reduce consumption. This could have lowered property crimes (to support addiction or to foster small quantity productions) and/or both property and violent crimes (committed while under the influence of this powerful substance). In this section, I propose a simple theoretical framework. This not only highlights the existence of the above-discussed tradeoff, but also aims to guide the empirical analysis.

3.1 Crystal Meth Prices

Before introducing the model I show descriptive evidence on crystal meth prices. Quarterly prices in 2007 U.S. dollars are aggregated at the national level. Prices are normalized per pure gram for three different weight categories.[22] These categories broadly correspond to three separate levels in the illegal-drug distributional chain (0.1 – 10g, 10 – 100g and >100g).

[Figure 2]

The first vertical line represents the 4th quarter of 2004. The second vertical line represents the third quarter 2005, when 70 percent of Early Adopters enacted OTC restrictions. Relative to the second quarter of 2005, the price for one gram of methamphetamine in quantities below 10 grams rose by 108 percent. The price for quantities between 10 grams and 100 grams rose by 70 percent.

[22] These are obtained from a public report "The Price and Purity of Illicit Drugs" (2008) by the Institute for Defense Analysis (IDA) for the Office of National Drug Control Policy (ONDCP). Price and purity estimates are derived from records in the STRIDE database. The Drug Enforcement Administration (DEA) maintains this database. The document, the data and the technical appendix describing the sampling and the manipulation procedure used are all public available at the following web page: http://www.whitehouse.gov/sites/default/files/ondcp/policy-and-research/bullet_1.pdf

The price for quantities exceeding 100 grams rose by 55 percent.[23] Overall, this evidence concurs to suggest that segments of extreme users plausibly experienced a significant shock to their cost of addiction. This effect, while difficult to quantify, is also corroborated by numerous ethnographic studies, describing drug addicts response to the implementation of the OTC reforms.[24]

3.2 The Model

I propose a theoretical framework capturing the salient aspects of heavy meth consumers: addiction, consumption and both an economic and pharmacological motive for crime. My model combines – in a novel stylized manner – a rational addiction framework à la Becker-Murphy (1988), with Becker's cost-benefit model of criminal behavior (1968).[25]

I analyze the decision process of a typical meth addict who lives two periods: pre-OTC restrictions (period 1) and post-OTC restrictions (period 2). In each period the agent faces two choices: i) how much crystal-methamphetamine to consume ($M \geq 0$) and ii) how much crime to commit to sustain his habit ($C \geq 0$). As previously described, meth users are particularly violent when under the influence. Also, acquisitive crimes to sustain the habit can lead to violent behavior against the victims (FBI, 2010). In this stylized framework, I model violent crime V as an increasing linear function of both usage and acquisitive crime: $V_t = F(M_t, C_t)$.

The intra-temporal utility function is as follows: $U_t = -(M_t - S_t)^2 - \theta C_t$. Here $t = 1, 2$ indexes the time period. The agent is exogenously allocated an initial level of addiction $S_1 > 0$. He suffers a quadratic loss when his consumption (M_t) deviates from his level of addiction (S_t). Drug addicts want to avoid withdrawal symptoms associated with under consumption. But, at the same time, they want to avoid overdosing, which can lead to severe convulsions, followed by circulatory and respiratory collapse, coma and death.[26] Initial consumption's decision affects the intertemporal problem: what is consumed in period 1 directly translates into the level of addiction in period 2 ($M_1 = S_2$).

Crime generates disutility for the the individual $\theta > 0$, because – for example – committing crime

[23] The graphical analysis also suggests a response in the production, showing a more homogeneous drop of around 35-40 percent in the purity of the substance in the same time frame. The plot of prices and purity of crack-cocaine (figure 7 bottom panel), heroin and powder cocaine does not reveal any significant pattern for these drugs. This figure is shown in Appendix A.

[24] Lopez (2014) interviewed 38 methamphetamine-using women convicted in Missouri. Nearly half of the women suggested that OTC restrictions made the purchase and manufacture meth more difficult: "when I was cooking anhydrous dope, we were doing [cooking] from 14, 15, 16 ounces at a time. Nowadays, people might make three or four grams at a time." This sometimes meant that the women would cook more frequently, even daily, which, of course, increased their risk of detection. The precursor restrictions also meant that women found it increasingly difficult to find methamphetamine for their own use. Similar evidence is found in Sexton et al. (2008). Some of the meth users in their sample agreed that the laws had restricted the illicit availability of PSE as well as meth production in their communities during the first year of their implementation. At the same time, many of these respondents had decreased their use and production of methamphetamine at the follow-up.

[25] To the extent of my knowledge, no theoretical model has linked drug addicition, usage and drug-mortivated crime in a unified framework.

[26] More information at: http://www.crystalmethaddiction.org/Crystal_Meth_Overdose.htm

embeds physical effort. At the same time, acquisitive crime is needed to sustain addiction: the agent either needs money to buy the drug within his close circle, or to buy chemical components that are needed during crystal meth production process. The agent maximizes the following inter-temporal problem $U_1 + \delta U_2$, with $\delta \in (0,1)$ being the agent's discount factor, choosing the optimal amount of meth-consumption and crime, under the following budget constraint: $p_t M_t = C_t$. Here $p_t > 0$ is crystal meth price.

The model captures the idea that meth users developed their addiction before the change in policy. When consuming and building up their habit, they did not internalize the possibility that prices would have dramatically increased in the future. For this reason, I differentiate between $E(p_2)$ (date 1 forecast of date 2 prices) and p_2 (crystal meth realized price in period 2). This implies that the agent is not perfectly forward looking (i.e. OTC restrictions represent an unexpected price shock for heavy users).[27] I solve the model by deriving consumption and crime in period 2, which depend on methamphetamine's consumption in period 1. Then, I solve the inter-temporal utility function, finding M_1^* and C_1^* as a function of expected meth price at time 2. Optimal solutions are:

Period 1 (Pre-Reform)

$$\begin{cases} M_1^* = S_1 - \frac{\theta(p_1+\delta E(p_2))}{2} \\ C_1^* = p_1(S_1 - \frac{\theta(p_1+\delta E(p_2))}{2}) \end{cases}$$

Finally, I compute optimal solutions for period 2, differentiating between $E(p_2)$ (date 1 forecast of date 2 prices) and p_2 (crystal meth realized price in period 2). Hence, the realized price in period 2 is different from its expectation. Optimal solutions are as follows:

Period 2 (Post-Reform)

$$\begin{cases} M_2^* = S_1 - \frac{\theta(p_1+\delta E(p_2)+p_2)}{2} \\ C_2^* = p_2(S_1 - \frac{\theta(p_1+\delta E(p_2))+p_2}{2}) \end{cases}$$

We also have that $V_t^* = F(M_t^*, C_t^*)$. Given that the model focuses on the behavior of a crystal meth addict, I assume the randomly allocated level of addiction S_1 "high enough": $S_1 > \frac{\theta(p_1+\delta E(p_2)+p_2)}{2}$. This avoids corner solutions.

3.3 Comparative Statics

I now discuss the main comparative statics deriving from the model. I focus on the effects of OTC restrictions, arising via a change in crystal meth prices, on optimal crystal meth consumption and criminal behavior.

Proposition 1. *An increase in methamphetamine prices monotonically decreases its consumption.*

Proof. By inspection: $(\partial M_t)/(\partial p_t) < 0, t = 1, 2$ □

[27] The model is also solved in the case of agent's perfect foresight: $E(p_2) = p_2$. Optimal solutions and comparative statics are qualitatively similar.

Interestingly, the model – while highlighting a monotonic effect on consumption – captures the existence of a non-monotonic effect of a price change on criminal behavior.

Proposition 2. *The effect on crime of an increase in meth prices exhibits an inverse U-relationship with respect to the price level.*

Proof. Direct differentiation. □

In period 2 it can be shown that[28]:

$$\begin{cases} (\partial C_2)/(\partial p_2) > 0 \iff p_2 < \tilde{p_2} \\ (\partial C_2)/(\partial p_2) \leq 0 \iff p_2 \geq \tilde{p_2} \end{cases}$$

With:

$$\tilde{p_2} = \frac{(2S_1 - \theta(p_1 + \delta E p_2))}{2\theta}$$

A rise in meth prices imposes an extra cost on addiction. For level of prices below $\tilde{p_2}$ this leads to an increase in crime. In this region, the expected marginal benefit deriving from criminal activity (meth usage closer to the level of satiation) is higher than its expected cost (effort to commit crime). Conversely, an increase in meth prices discourages criminal activity above $\tilde{p_2}$. Note that an increase in the initial level of addiction S_1 pushes $\tilde{p_2}$ to the right: an extreme addict will resist more to an increase in prices before reducing his level of criminal activity. The opposite argument applies for an increase θ that decreases the threshold-price $\tilde{p_2}$. The higher the cost committing of crime, the smaller the region where an increase in price induces more criminal activity. Finally, an increase in p_1 and $E(p_2)$ pushes the threshold to the left. This happens because the reduction in meth consumption in period 1 lowers the desire for drug in period 2. This dynamic widens the region where a rise in meth prices discourages criminal activity. I now move to discuss proposition 3.

Proposition 3. *The effects of a change in prices on crime can be positive or negative, depending on the distribution of parameters. Nevertheless, there will always be a price "high-enough" for which* $C_2^* < C_1^*$.

Proof. $C_2^* \leq C_1^*$ implies that:

$$\theta p_2^2 + p_2[\theta(p_1 + \delta E(p_2)) - 2S_1] + p_1[2S_1 - \theta(p_1 + \delta E(p_2))] \geq 0$$

$S_1 > \frac{\theta(p_1+\delta E(p_2)+p_2)}{2}$ and $\theta > 0$ implies that the solutions of this quadratic inequality are two positive square roots (when the determinant is greater than zero). □

Proposition 3 provides a rationale for the main empirical finding of the paper. In fact, this proposition ensures that – independently from the initial level of addiction S_1 there will always be a realized price p_2 for which agent's criminal activity in period 2 (post-regulation) falls below the level of criminal activity in period 1 (pre-regulation).

[28] A similar reasoning applies for period 1.

Proposition 1 predicts that OTC restrictions will reduce meth consumption. It follows that violent crime directly arising under the influence should be deterred if crystal meth consumption decreases. Note that the overall effect of OTC restrictions on violent crime, via a change in prices, is still ambiguous. In fact, following proposition 2, this will depend from the sign and magnitude of the effect of a change in meth prices on the proliferation of acquisitive crimes (which can be positive or negative, depending on whether the realized price p_2 is above or below $\tilde{p_2}$).

4 Data Sources and Identification Strategy

This section describes the main data sources. Then, it introduces the central DD design 1) discussing the extent of pre-intervention differences between treated and control states and 2) arguing the validity of the critical identifying assumption of conditional parallel pre-trends.

4.1 Data Sources

I assembled an annual panel dataset, covering a 10-year period (2001-2010), encompassing 50 states and 2,200 counties, and representing 70 percent of U.S. counties and 94 percent of the U.S. population.[29]

County-level information on reported crimes, drugs-related arrests, number of police officers with arrest powers and civilian employees is accessed through the National Archive of Criminal Justice Data (NACJD).[30] County-level files are created by NACJD, based on agency records in a file obtained from the FBI that also provides aggregated county totals. NACJD imputes missing data and then aggregates the data to the county level.[31]

The "Uniform Crime Reporting Program Data: Supplementary Homicide Reports," accessed through the NAJCD, provides incident-based information on criminal homicides reported to the police. This database contains information describing the victim, the offender, the weapon used,

[29] The final database is obtained by merging and constructing county-level information from several sources described in this section. The cross-sectional size of the final dataset is determined by missing observations on all datasets (FBI, DEA and all databases from the U.S. Census Bureau and Bureau of Labor Statistics-Current Population) and the presence of data corruption and differences in counties' names across sources. Data on crime are merged from 2001 (one year after the Methamphetamine Anti-Proliferation Act of 2000 was implemented, and the year Utah authorized the first state law) to 2010. Data on meth-lab seizures are publicly available from 2004. The main empirical analysis focuses on the period from 2001 to 2006 (the year in which CMEA federal act was implemented).

[30] Data are freely downloadable at: http://www.icpsr.umich.edu/icpsrweb/content/NACJD/guides/ucr.html#desc_cl (accessed date: September 2012).

[31] In the FBI's Uniform Crime Reporting (UCR) Program, property crime includes burglary, larceny theft, motor vehicle theft and arson. The property crime category includes arson because the offense involves the destruction of property; however, arson victims may be subjected to force. Because of limited participation and varying collection procedures by local law enforcement agencies, only limited data are available for arson. In the FBI's Uniform Crime Reporting (UCR) Program, violent crime is composed of four offenses: murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault. Violent crimes are defined in the UCR Program as those offenses that involve force or threat of force.

and (when known by investigators) the different circumstances surrounding the homicide.[32]

The National Clandestine Laboratory Register, provided by the U.S. Department of Justice, contains dates and addresses of locations where law enforcement agencies reported finding chemicals or other items that indicated the presence of either clandestine drug laboratories or dumpsites.[33] I use this information to generate a county-level, annual measure of the number of meth labs seized by the local enforcement agencies. These data are available from 2004.

The empirical analysis uses a wide set of county-level, time-varying socio-economic controls. These are obtained from the U.S. Census Bureau and from the Bureau of Labor Statistics-Current Population.[34] These variables, all summary statistics and other data sources will be discussed when relevant for the analysis.

4.2 Main DD Design: Empirical Strategy Discussion

The main DD strategy estimates the differences in criminal activity between counties belonging to 1) Early Adopter states, that implemented OTC regulations in 2005, and 2) CMEA Only states, which did not approve any regulation, but were subject only to the CMEA federal act. Given that the CMEA federal act was implemented nationwide in the last part of 2006, I limit this DD analysis to the period 2001 – 2006.

The endogenous decision of Early Adopter states to restrict the access of methamphetamine precursors needs to be addressed. A necessary step toward understanding underlying reasons is provided by the analysis of pre-intervention differences between Early Adopters and CMEA Only states.

Tables I (A, B and C) summarize means and differences of relevant variables. In these tables, columns (1) and (2) report the mean of each variable for CMEA Only and Early Adopter states, respectively. Column (3) shows the difference between (1) and (2). I report 10 percent, 5 percent, and 1 percent significance levels. Means are computed in the pre-intervention period, from 2001 to 2004, by county or by state. Variables are normalized per 100,000 inhabitants, when meaningful.

[Tables I (A-B-C)]

[32]These data are reported at the FBI agency level. I use crosswalks FBI data – accessed through NAJCD – to match police agencies to U.S. counties. The crosswalk file is designed to provide geographic and other identification information for each record included in either the FBI's Uniform Crime Reporting (UCR) program files or in the Bureau of Justice Statistics' Census of State and Local Law Enforcement Agencies (CSLLEA). In less than 2 percent of cases, agencies' territory is included in multiple counties. Due to the difficulty of assigning the homicide category to the correct county, I drop these observations when collapsing agencies measures into county-level measure of different circumstances surrounding the homicide.

[33]These data are publicly available at: http://www.dea.gov/clan-lab/clan-lab.shtml. (Accessed Date: September 2013). Data on labs and on estimates of price and purity are constructed from the DEA's System to Retrieve Information from Drug Evidence (STRIDE) dataset. STRIDE is a forensic database populated primarily with DEA seizures and purchases that were sent to the lab for analysis. This dataset has been criticized because the recorded transactions are unlikely to be representative of all drug transactions (ONDCP 2004c; Joel L. Horowitz 2001). Nevertheless, STRIDE represents the best measures of the purity and prices of illegal drugs in the United States (Dobkin and Nicosia, 2009).

[34]I use http://censtats.census.gov/usa/usa.shtml, (accessed date: December 2012).

Table I-A reveals that CMEA Only states (states that did not adopt any OTC regulations of their own) were characterized by significantly less methamphetamine production. This information is summarized by a difference in meth labs seizures of 5.7 per 100,000 inhabitants. Similarly, these states were experiencing significantly fewer hospitalizations (always expressed per 100,000 people) due to methamphetamine abuse (-46.4), amphetamine abuse (-23), drug-related arrests for sale (-11.1), and possession (-23.8) of other-dangerous non-narcotics (the FBI category including crystal methamphetamines), and for sale and possession of synthetic narcotics (-8.1 and -14.2). At the same time, CMEA Only states were characterized by significantly more arrests for: possession of marijuana (+53), sale and possession of cocaine, heroin, and derivatives (+25.5 and +33.8). CMEA Only states also experienced significantly more hospitalizations due to alcohol, cocaine, heroin, and over-the-counter medicines.[35]

The presence of significant differences in the use and penetration of distinct illegal drugs in different U.S. states provides a rationale for the take up of OTC restrictions from Early Adopter states. Nevertheless, the existence of such differences does not undermine the validity of the results obtained using a DD estimator, if the assumption of conditional parallel pre-trends in the outcome variable is satisfied. Figure 2 investigates the merits of this assumption. I show the evolution in criminal activity – for both treated and control states – from 2001 to 2006, the period of analysis in this empirical exercise.

[Figure 3]

Figure 3 reveals a reassuring pattern of criminal activity before states' intervention for larcenies, burglaries, murders, and assaults. It also uncovers a sharp reduction in burglaries and larcenies in 2005 and in 2006, and a slight post-regulation reduction in Early Adopter states for murders and aggravated assaults.[36] Figure 3 also shows a slight increase of violent crimes in CMEA Only states, after the enactment of OTC restrictions. This might indicate the presence of geographical relocation across states' borders, a hypothesis explicitly tested in the continuation of the paper.

5 Results

This section reports results of the main DD design. I use a reduced form approach to estimate the effects of OTC restrictions on crime. First, I show baseline results. Then, I present and discuss the event-study analysis. Third, I report robustness checks. Fourth, I perform two distinct triple-differences designs. These aim to uncover significant differential impacts effects across treated counties. Finally, I present two placebo tests on cyber and "white-collar" crimes

[35]The evidence on pre-existing differences in criminal activity is more ambiguous (Table I-B). CMEA Only states were characterized by fewer larcenies and burglaries (-301.9 and -172.59) but by a higher level of robberies (+35.68). No significant differences are detected for murders or aggravated assaults. Counties belonging to control states experiencing fewer rapes (-2.13) but more episodes of arsons (+4.05). Table I-C summarizes pre-intervention differences of all socio-economic controls used in the analysis. I omit this discussion for brevity considerations.

[36]The validity of the assumption of conditional parallel trends is also supported by the event-study analysis shown in the next section.

5.1 Baseline Results

I use the following DD estimating equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + (Treated * Post)\beta_1 + \varepsilon_{c,s,t} \tag{5.1}$$

Here the subscript c indicates the county, s the state and t the year. Outcomes of interest are reported crimes, expressed as $log(1 + x)$. The measure of each crime x is normalized per 100,000 people. The analysis focuses on β_1. This is the coefficient associated with the interaction between Treated (an indicator variable taking the value of 1 if the county belongs to an Early Adopter state and zero if it belongs to a CMEA Only state) and Post (an indicator variable taking the value of 1 for years 2005 and 2006, 0 otherwise). Standard errors are clustered at the state level.[37]

The estimating regression (1) includes: 1) county fixed effects α_c, which absorb time-invariant unobserved heterogeneity across counties; 2) year fixed effects γ_t, capturing common shocks; and 3) a vector of county time-varying socioeconomic controls $X'_{c,s,t}$. These are: income per capita, percentage of people below the poverty line, unemployment, social security recipients, average monthly payment per subsidy, commercial banks and saving institutions per 100,000 inhabitants, amount of banking and saving deposits, and population density.

[Tables II (A-B)]

Tables II-A and II-B show the results, with the baseline specification only including year FE and county FE alongside the interaction term Treated*Post.

DD estimates reveal a significant reduction of around 7 to 7.5 percent for larceny and burglary and 13 percent for murder. P-values are below the 5 percent significance level. For aggravated assault, rape and robbery, I detect negative coefficients of similar magnitude (-5 percent, -7.8 percent and -8.3 percent, respectively), however, these are imprecisely estimated. No effect is detected for arson or motor vehicle theft.

[Table III]

Table III present results for larceny, burglary, assault and murder. These are obtained using equation (1) and including all county-level, time-varying observables. Results are similar in magnitude and precision to the baseline specification. The estimated coefficients are: -8.1 percent for larceny, -7.4 percent for burglary and -10 percent for murder. These coefficients are precisely estimated with a p-value below 5 percent.[38]

[37] The sample includes 30 treated states and 8 control states

[38] Results for all other crimes are similar in terms of size and magnitude to the ones presented in Table III panel B. Results are omitted for brevity considerations, and are available upon request

5.2 Event-study Analysis

This section discusses and presents the results for the event-study analysis. I use the following estimating equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + \sum_{j=2001}^{2006} (Treated * Year_j)\, \beta_{2,j} + \varepsilon_{c,s,t} \tag{5.2}$$

The analysis focuses on $\beta_{2,j}$. These are the coefficients associated with the interaction of Treated (an indicator variable taking the value of 1 if the county belongs to an Early Adopter state and zero otherwise) and $Year_j$ (an indicator variable for each year). The omitted category is the interaction of Treated and the dummy for 2004, which is the year preceding the enactment of OTC restriction in Early Adopter states. Other details are as in equation (1).

This estimation technique offers several advantages. In particular, while explicitly testing for the presence of significant differential pre-trends in criminal activity, it allows for a flexible non-parametric estimation of the effects of OTC restrictions on crime. Indeed, this might have had differential effects in the year or the implementation of the laws, or in the year after. Tables IV-A and IV-B present the results.

[Tables IV (A-B)]

For larceny, I detect a reduction of 10.4 percent in the year 2005 and of 12.7 percent in the year 2006. Coefficients are precisely estimated, always below the 1 percent significance level. Pre-intervention coefficients grow in magnitude (from -0.04 in 2001 to -0.02 in 2004). A significant coefficient is detected only in 2002, hence three years before intervention. For burglary, I detect reductions of 8 percent to 9.8 percent in the years 2005 and 2006, respectively. Significance levels are below 5 percent. No significant differential pre-trend is detected. Results for aggravated assault are reported in columns (3). I detect a decrease of 7.7 percent in 2005, significant at the 10 percent level. The coefficient in year 2006 is around -4.3 percent. This is imprecisely estimated. For murder, columns (4), I detect a decrease of 16 percent in 2005 and 7 percent in 2006. The coefficient in 2005 has a significance level below 5 percent, while the coefficient in 2006 is imprecisely estimated.[39] For aggravated assault and murder, no significant pre-intervention pattern is detected. Figure 4 plots the coefficients of the event-study together with 95 percent confidence intervals reported.

[Figure 4]

Table IV-B presents the results obtained through estimating equation (2) for robbery, rape, arson and motor vehicle theft. No significant effect is detected, with the exception of rape, where I detect a reduction of 14.4 percent in 2005 (significant at the 10 percent level). The presence of a significant coefficient of -10 percent in 2004 imposes caution in the interpretation of the estimates for rape.

[39] Using this specification no significant effect is detected for motor-vehicle theft, robbery, arson or rape.

5.3 Robustness Checks

Tables V (A to E) present the main robustness checks for the event-study analysis. Table V-A shows the results when I add to the baseline specification measures of police officers with arrest powers and civilian employees. These controls, while deepening the extent of the analysis potentially capturing time-varying confounding factors, are not included in the baseline specification. These might be considered as potential outcomes of policies implemented to eradicate methamphetamine production. Table V-A shows the results. Coefficients and the significance levels are stable across crimes and are almost identical to the baseline specification.

[Tables V (A-E)]

Table V-B includes state-specific linear trends. This specification increases the magnitude of the estimates for property and violent crimes (i.e. estimates are more negative). This result allows for a variety of interpretations. State-specific trends might be an unobserved confounder in the analysis. This is the case if the endogenous decision to adopt OTC restrictions is positively correlated with linear crime trends. In other words, if factors associated with rising crime increased the pressure for the reform, the inclusion of state-specific time trends, while absorbing this effect, would move estimates down. From an econometric perspective, the inclusion of state-specific trends plausibly generates collinearity with the interactions of interest (that uses a state-by-year variation). This potentially amplifies the effects of the laws on criminal activity. Despite the difficulty of disentangling these separate effects, I find it encouraging that the inclusion of state-specific trends strengthens (rather than weakens) the crime-reducing effects of OTC restrictions.[40]

Table V-C shows the results when I weight the regression by the coverage indicator reported by the agency, a measure of the reliability of the information on crime available to the researcher.[41] Results are stable to this specification.

Tables V-D and V-E show the results where I use: 1) the linear measure of crime per 100,000 people as outcome variable, or 2) the count measure of crimes as outcome variable using the Poisson fixed-effects estimator. This robustness check is performed to examine the sensitivity of the estimates, due to over-dispersion of the outcome variables (particularly acute to the case of murder, with a mean of 3.2 and a standard deviation of 5.7). Results do not depend from the functional form used and are robust to both these specifications.

[40] Almost identical results are obtained when state-specific quadratic trends are included. Results are omitted for brevity considerations only. I perform this same robustness for the baseline difference in differences, where I use the interaction term treated*post. The inclusion of state-specific linear trends produces essentially the same results that are shown in table A2 of the appendix.

[41] The Coverage Indicator ranges from 100, indicating that all ORIs (originating agency identifiers) in the county reported for 12 months in the year, to 0, indicating that all data in the county are based on estimates, not reported data.

5.4 Psychological or Systemic Channel?

In the attempt to answer this question I use FBI county-level information on homicide circumstances.[42] Table VI shows all the FBI categories of circumstances leading to murders, number of episodes for the period spanning 2001 to 2006 and relative frequency.

[Table VI]

I have grouped homicide circumstances in 5 broader crime categories: 1) theft, 2) sexual intercourse, 3) gangs and drug trafficking, 4) brawls and violent altercations and 5) crimes due to negligence. As in the preceding analysis, I use the estimating equation (2).

Noteworthy, the exit from the market of a multitude of meth-producers controlling low and medium capacity labs (Dobkin et al., 2014) might have reduced the competition among drug dealers. This, among other reasons, could have lowered the systemic violence associated with the sale of crystal methamphetamines. This channel, rather than the psychological one associated with pure consumption, might explain the drop in murders and aggravated assaults following OTC restrictions. Results are shown in table VII.

[Table VII]

I detect a reduction of 8.2 percent for murders connected to brawls and violent altercations in the year 2005. This coefficient is significant at the 5 percent level. No significant effect is detected on other homicide circumstances. In particular, I do not observe any significant change on the violence typically associated with drug trafficking (expressed by homicides due to narcotic drug laws' offense, gangland killings and juvenile gang killings). This analysis seems to supports medical evidence on the criminogenic effects of crystal-meth. OTC restrictions have reduced the episodes of violent altercations terminated with a murder. These episodes happen with higher probability when the offender is under the influence of this powerful neurotoxic drug (McKetin et al., 2014). Conversely, this analysis suggests that the reduction in violent crimes it is not driven by a reduction in the systemic violence. This is typically associated with major illegal drugs markets, such as the one for marijuana, cocaine or heroin (DEA, 2010).

5.5 Heterogeneity Analysis: Two Triple DD Designs

Small clandestine production and abuse of crystal meth typically takes place in rural, sparsely populated counties. This partly reflects meth producers' needs: the methamphetamine production process, which generates toxic fumes and frequent explosions, must be hidden from the public and from law enforcement officers (DEA, 2006).

[42] Data on violent crime arising under the influence of crystal meth are unavailable. NIBRS data contain information on whether the offender was perceived to be under the influence of a drug, by the victim of the crime. Unfortunately, NIBRS data are characterized by extreme low level of reporting by U.S. Agencies. In 2001, only 18% of agencies in 21 states reported criminal information to NIBRS. Moreover, under-reporting exists also within agency. This problem, together with the huge number of missing values makes the analysis via NIBRS data unviable.

[Figure 5]

Figure 5 shows a map of the distribution of seized labs in the United States in 2004. Categories expressed in deciles, for illustrative purposes only. The production of methamphetamine is spread across the entire country, with higher concentration in Missouri, Tennessee, Arkansas, Kansas and Indiana. Figure 6 investigates this relationship, showing the scatterplot and the quadratic fit of the number of methamphetamine labs seized by law enforcement agencies in 2004 in each county, normalized per 100,000 people, and population density in 2001.[43] As expected, it illustrates that a higher concentration of meth lab seizures is found in sparsely populated, rural counties.

[Figure 6]

This leads me to explore the presence of significant differential effect of the laws within treated states. I implement two distinct triple differences designs. First, I use as a third interaction a county population's density. Then, I use as a third interaction term the pre-reform concentration of meth labs seized by law enforcement agencies. I employ the following estimating equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + (T * P)\beta_1 + (D * P)\beta_2 + (T * P * D)\beta_3 + \varepsilon_{c,s,t} \tag{5.3}$$

Here T=Treated, P=Post (as in the baseline DD design, equation (1)) and D=population density fixed in 2001 (first design) and meth labs seized fixed in 2004 (second design).[44] Table VIII shows the results for the first design, where I include county population density.

[Table VIII]

The triple interaction term has a positive coefficient in all specifications. For burglary the coefficient of 0.018 is significant at the 5 percent level. For aggravated assault the coefficient of 0.015 is significant at the 10 percent level; for murder the coefficient of 0.04 is significant at the 1 percent level. This specification captures the fact that the crime-reducing effect of the laws is significantly lower in treated, densely populated counties.

In the second experimental design, I use as a third interaction term the county-level number of meth lab seizures normalized per 100,000 people (fixed in 2004). This approximates the underlying, pre-determined local production of crystal meth. The estimating equation is otherwise identical to (3). Table IX shows the results.

[Table IX]

I detect a negative coefficient of the triple interaction term, significant at the 5 percent level for larceny and assault (-0.01 and -0.04). For murder, the triple interaction is high in magnitude (-0.048)

[43] I use density in 2001 and meth lab seizures in 2004 because those are the first years for which data for each category are available.

[44] The interaction between density and treated is absorbed by county FE.

but not significantly different from 0. To interpret the results, I note that a one-unit increase in the pre-intervention normalized measure of labs per 100,000 people generates an additional 1.3 percent decrease in larcenies and an additional 3.8 percent decrease in aggravated assaults. As expected, this analysis suggests that the enactment of OTC restrictions reduced crime more in treated rural counties with a higher predetermined concentration of domestic methamphetamine production, and, plausibly, a greater presence of extreme abusers.

5.6 Two Placebo Tests: Cyber & Financial Crime

In this section I develop placebo tests on two distinct crime categories that, reasonably, should not have been affected by the enactment of OTC restrictions: cybercrime and financial "white-collar" crime. These are unlikely to be perpetrated by abusers who exhibit substance-induced psychosis, mood disturbances, and paranoia.

Cybercrime are fraud types such as auction fraud, non-delivery, and credit/debit card fraud, as well as non-fraudulent complaints, such as computer intrusions and spam/unsolicited e-mail. State-level measures of cybercrime are obtained from the annual Internet crime report prepared by the National White Collar Crime Center and the FBI.[45] Due to the transnational nature of this crime, I have analyzed both the state-level measures of complainants and perpetrators per 100,000 people. Financial institution fraud and failure investigations (FIF) include mortgage and loan fraud, insider fraud, check fraud, counterfeit negotiable instruments and check kiting. These data are obtained through the FBI web portal.[46] These annual data are at the FBI field office level and are distinct by indictments and convictions.

[Figure 7]

Figure 7 shows the results of estimating equation (2) for both categories of crime. To perform this analysis, I have collapsed the mean of socio-economic controls at the state-year level. Due to the placebo nature of the exercise, I plot a more conservative confidence interval of 90 percent. As expected, no significant effect is detected for cyber and financial crimes.[47]

6 Exploring the Mechanisms

This section explores potential mechanisms behind the reduction in crime. A major drawback for this study is the lack of county or state-level data on crystal-meth consumption. Nonetheless, figure 8 shows two informative separate pieces of descriptive evidence.

[Figure 8]

[45] These are accessible at http://www.ic3.gov/media/annualreports.aspx
[46] Accessible at https://www.fbi.gov/stats-services/crimestats
[47] Tables are omitted for brevity considerations, and are available upon request.

The left-hand figure shows trends of lifetime prevalence of crystal methamphetamines use in a population of 12th graders in the United States. Data is obtained from "Monitoring the Future" an ongoing study of the behaviors, attitudes, and values of American secondary school students, college students, and young adults.[48] Each year, a total of approximately 50,000 8th, 10th and 12th grade students are surveyed. We observe a drop in crystal methamphetamine's lifetime prevalence of almost 30 percent from 2004 to 2005.

On the right hand side, I plot data from Drug Testing Index Archives of Quest Diagnostics, the largest provider of workplace drug tests in the U.S.[49] We observe a reduction of 15.2 percent in 2005 and 35.7 percent in 2006 with respect to the year 2004. The official documentation of Quest Diagnostics further corroborates Testable Implication 1:

> "*Methamphetamine, the most commonly abused type of amphetamine, increased in production and trafficking during the 1990's to become the most prevalent illegally manufactured synthetic drug in the United States. Analysis of the Quest Diagnostics Drug Testing Index, released semi-annually, suggests that efforts to reduce illicit, clandestine production of methamphetamine may be having an impact on workplace positive tests for the drug.*"

If these people curbed the intensive/extensive margin of consumption, they plausibly experienced physical and mental issues. I test this hypothesis using the Treatment Episode Data Set (TEDS). This database is maintained by the Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration (SAMHSA). The TEDS system includes state level records for some 1.5 million substance abuse treatment admissions annually. While TEDS does not represent the total national demand for substance abuse treatment, it contains a significant proportion of all admissions. These are voluntary admissions for detoxification, rehabilitation and ambulatory. I use an estimating equation similar to equation (1). The only difference stems from the fact that TEDS data and all socioeconomic controls are reported the state-year level. Table X presents separate results for hospitalizations due to meth, alcohol, heroin, cocaine, marijuana, and amphetamines.

[48] Monitoring the Future (MTF) has surveyed nationally representative samples of full-time college students one to four years beyond high school each year for 35 years, starting in 1980. The annual samples of college students have ranged between 1,000 and 1,500 per year. MTF also conducts an annual national survey of high school seniors, from which a random, nationally representative sub-sample is drawn for follow-up by mail in future years. Follow-up respondents one to four years past high school and who report being enrolled in college full-time comprise the college student sample. They are not drawn from particular colleges or universities, which helps to make the sample more representative of the wide range of two- and four-year institutions of higher education MTF is an investigator-initiated research undertaking, conceived and conducted by a group of research professors at the University of Michigan's Institute for Social Research, and funded under a series of peer-reviewed, competitive research grants from the National Institute on Drug Abuse.

[49] Freely available at http://www.questdiagnostics.com/home/physicians/health-trends/drug-testing/archives.html. The workplace drug tests are not administered to a random sample of workers. Although some of the tests are random, the majority of the tests are conducted for a particular reason such as pre-employment screening, accidents, or "for cause". Tests that are done "for cause" are more likely to return a positive finding than tests conducted for other reasons (Dobkin et al, 2014).

[Tables X]

I detect an increase of 34% for hospitalizations due to methamphetamines, significant at the 5% level. The effect is isolated only to crystal methamphetamines. No effect is detected on hospitalizations related to alcohol or other illegal drugs.[50]

I also analyze data from The Drug Abuse Warning Network (DAWN). DAWN provides nationally representative patient demographic and visit-level information on emergency department (ED) visits. These visits can result from: substance misuse or abuse, adverse reactions to drugs taken as prescribed or directed, accidental ingestion of drugs, drug-related suicide attempts, and admissions for detox. Distinct information exists for several illegal drugs.[51]

[Figure 9]

Figure 9 shows national level data from 2004 to 2007. I observe a general decrease in ED meth-related treatment throughout the US (top figure). Interestingly, consistent with testable implication 2, I notice a peak in 2005 for emergency treatments associated with crystal-meth detox. In 2005 there has been an increase of 31 percent with respect to the pre-reform year in 2004. I also observe an increase in 2005 and 2006 in emergency treatments due to suicides attempts arising from methamphetamine use (+20 percent in 2005 and +6.5 percent in 2006 with respect to year 2004). Suicidal tendency is a condition medically associated with meth withdrawal.

Finally, I investigate the presence of potential heterogeneous impacts of the laws across U.S. states. I estimate the following regression:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + \sum_{j=1}^{30} (Treated_j * Post)\,\beta_{1,j} + \varepsilon_{c,s,t}$$

I show the results of this specification in figure 10 for larceny and murder. I plot 30 states-specific coefficients obtained from a regression that interacts the variable "Post" with each state dummy.[52]

[Figure 10]

Figure 10 top-panel shows the plot of the coefficients for larceny and murder for each of the 30 treated states. This figure shows heterogeneous effects on both property and violent crimes. Four

[50] Medical episodes due to meth abuse represent around 6.5 percent of the total number of hospitalizations for alcohol and other illegal substances. 183,363 of these cases where recorded in TEDS in the year 2004. Online Appendix A contains the details on the 8 different type of medical treatment recorded in TEDS and relative frequency for crystal meth episodes.

[51] The Drug Abuse Warning Network, or DAWN, collects data from a nationally representative sample of hospitals throughout the United States, including Alaska and Hawaii. Non-Federal, short-stay, general surgical and medical hospitals with a 24-hour ED are eligible for inclusion.

[52] I impose equal to zero all the interactions between "Post" and the 8 dummy variables of each control state. Results on all other crimes are qualitatively similar. Tables are omitted for brevity considerations and are available upon request.

U.S. states experienced a positive and significant effect on larceny due to OTC restrictions (Indiana, Missouri, Montana, Virginia, West Virginia) with Alabama, Louisiana and Hawaii displaying the top reduction. Three states display a significant increase in homicides (Arkansas, Delaware and Hawaii). It is extremely difficult to investigate the driving forces behind this heterogeneity in the impact. I do an initial attempt plotting the coefficients obtained from regression (4) in the y-axis, and the log of the number of hospitalizations due to meth-abuse in the x-axis. The bottom panel of figure X shows negative correlations between the estimated coefficients and the normalized measure of predetermined meth-abuse at the state-level. This evidence suggests that the reduction in criminal activity is stronger in U.S. states with a higher pre-existing concentration of extreme meth addicts. Deepening the understanding of this heterogeneity seems to represent a promising, and policy–relevant, direction for future research.

7 Concluding Remarks

This paper examines the methamphetamine-crime link, analyzing the effect of regulations that limited the access to common cold medications containing ephedrine or pseudoephedrine. These are key precursors needed by extreme users to manufacture crystal meth, often at very small scales, mainly to sustain their habit. The dramatic increase in the effective costs of domestic production isolates arguably exogenous variation in methamphetamine exposure of potentially dangerous, extreme users. I take advantage of the variation in i) timing of the implementation of state and federal policies, ii) prevalence of distinct types of illegal drugs used in different areas of the United States. I perform several experimental designs on a newly assembled panel dataset including county-level data from the DEA and FBI, and covering nearly the entire U.S. population.

I develop an original model combining a rational addiction framework à la Becker-Murphy (1988), with Becker's cost-benefit model of criminal behavior (1968). The model provides guidance for the empirical analysis, capturing salient aspects of heavy meth consumers: addiction, consumption and both an economic and pharmacological motive for crime. Two central findings emerge: i) a change in prices, while deterring abuse, leads to a non-monotonic effect on criminal behavior; ii) drug-related crime declines for 'sufficiently' high prices. I find that these regulations led to a sharp decline of 5 percent to 10 percent in property and violent crimes. The effects are stronger in rural counties, where meth-production and abuse is typically concentrated, and law enforcement officials have described it as reaching epidemic proportions. I also detect a decline in murders due to violent altercations, plausibly associated with the psychotic effects arising from drug use; but no effect on homicides associated with systemic violence (typical of more professional drug markets). The analysis of the underlying mechanisms reveals a potential a drop in methamphetamine consumption among heavy users, an increase in methamphetamine-related hospitalizations associated with detox, withdrawal symptoms and rehabilitation; and heterogeneous and non-monotonic effects on criminal activity across U.S. states. Overall, this work supports the hypothesis that extreme addicts reduced their consumption, or quit using it altogether. Crime is a way that addicts pay for their drug habit (economic channel). It also is an outgrowth of the erratic and violent behavior characteristic of extreme addicts (psychological channel). When the consumption among extreme users declined, so did their related criminal activities.

Policy Implications An ongoing policy debate is centered on the classification of nonprescription medicines containing ephedrine or pseudoephedrine (PSE), into prescription only drugs. Oregon (as of July 2006) and Mississippi (as of July 2010) are the only two U.S. states that have classified pseudoephedrine and ephedrine as Schedule III substances. In these states, customers require a medical prescription for obtaining medicines potentially usable to manufacture crystal meth.[53] According to a recent Government Accountability Office report (2013), the debate is of central importance but of difficult resolution. This is mainly due to i) the presence of significant interests arising from different parties (in primis pharmaceutical companies and medical patients) and ii) the unsolved persistent problem related to meth abuse and domestic production.[54] Between 2010 and January 2013, at least sixty-nine bills were introduced in eighteen U.S. states that would require consumers to obtain a prescription in order to purchase PSE products. Most of these bills were referred to specific committees; none of these has been approved yet. My work – by detecting a sharp reduction in abuse and criminal activity following the OTC reforms – informs this debate, emphasizing the need of taking into account potential changes in criminal activity deriving from further restricting the access to crystal meth chemical precursors.

This paper also informs policy-makers outside the United States about potential links between methamphetamine's extreme use, criminal behavior and laws restricting the access the meth precursors. Eastern Europe, Africa, South East Asia, Middle East and Australia are experiencing a giant rise of the so called "crystal meth epidemic", facing all the negative consequences associated with drug abuse and criminal behavior (UNODC, 2015). The spread of this dangerous phenomenon is closely connected to the central aspect analyzed in this paper: the simplicity of crystal meth production process, typically performed by heavy users of this extremely powerful, neurotoxic, addictive substance.[55]

On a broader perspective, this work suggests that similar policies should consider the hierarchical structure and the pre-existing level of competition of the targeted drug market. Major producers and dealers – such as those trafficking heroin or cocaine – might respond by intensifying the level of systemic violence (Dell, 2014), smuggling other illegal substances, or changing territory. By contrast, this does not seem to happen in a highly localized meth market, arguably because its main actors are extreme addicts, who mainly care about consumption.

[53] More info at: http://www.cdc.gov/phlp/docs/pseudo-brief112013.pdf (Accessed date: August 2013).

[54] Seizure data, law enforcement reporting, and localized treatment information all indicate methamphetamine trafficking and abuse continues to increase throughout the nation. According to the 2014 National Drug Threat Assessment (NDTS), 31.8 percent of responding agencies indicated methamphetamine was the greatest drug threat in their areas. Also, 40.6 percent of responding agencies indicated that methamphetamine is highly available, meaning the drug is easily obtained at any time. As in previous years, abuse and availability are much higher in the Western United States. More information is available at: http://www.dea.gov/resource-center/dir-ndta-unclass.pdf.

[55] More information about the spread of methamphetamine can be found from numerous sources. See: https://data.unodc.org/#state:1, http://www.bbc.co.uk/news/world-australia-32200684, https://news.vice.com/article/meth-trafficking-has-exploded-throughout-asia-despite-hardline-laws.

The present work suggests that limiting the access to addictive drugs might lead to heterogeneous effects on crime, which could arise for several reasons. 'Hard-drugs' might induce relatively more crime i) when users are under the influence (e.g. stimulants such as crack cocaine, amphetamines and "bath salts") ii) or on withdrawal (e.g. narcotics such as opium, morphine and heroin). A key role could be played by a non-linear elasticity of demand to changes in drug prices, affecting crime differently within different price ranges. Ultimately, this paper suggests that embedding the criminogenic effects of drug abuse within the model of Becker (1968) might provide a richer framework to study potential criminal responses to distinct drug-interventions. Very little is known in this area, providing a fertile ground for future research.

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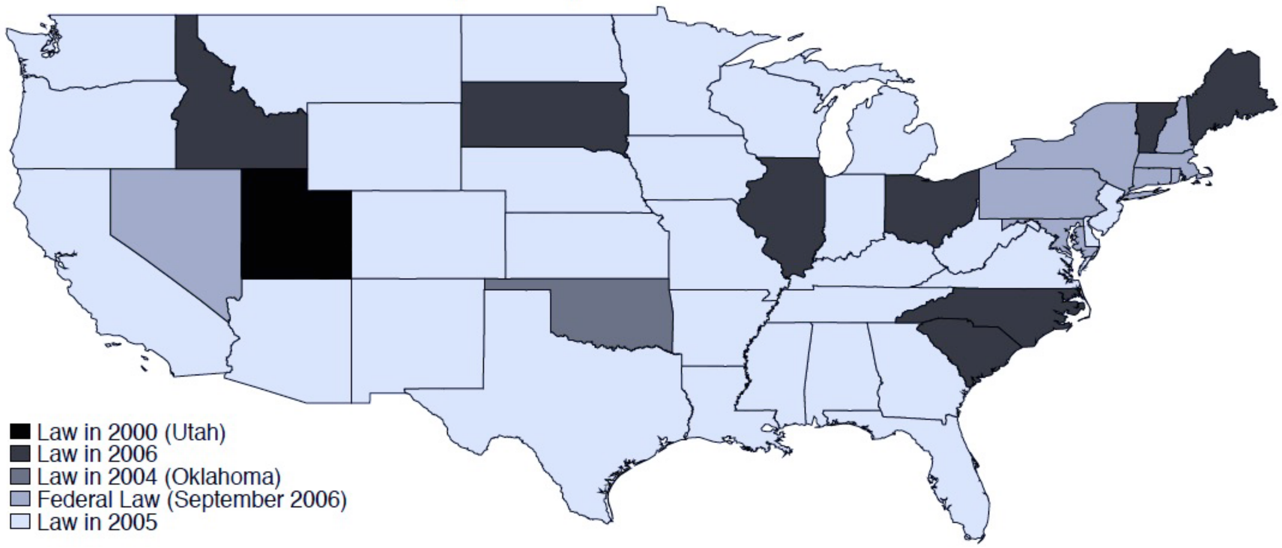
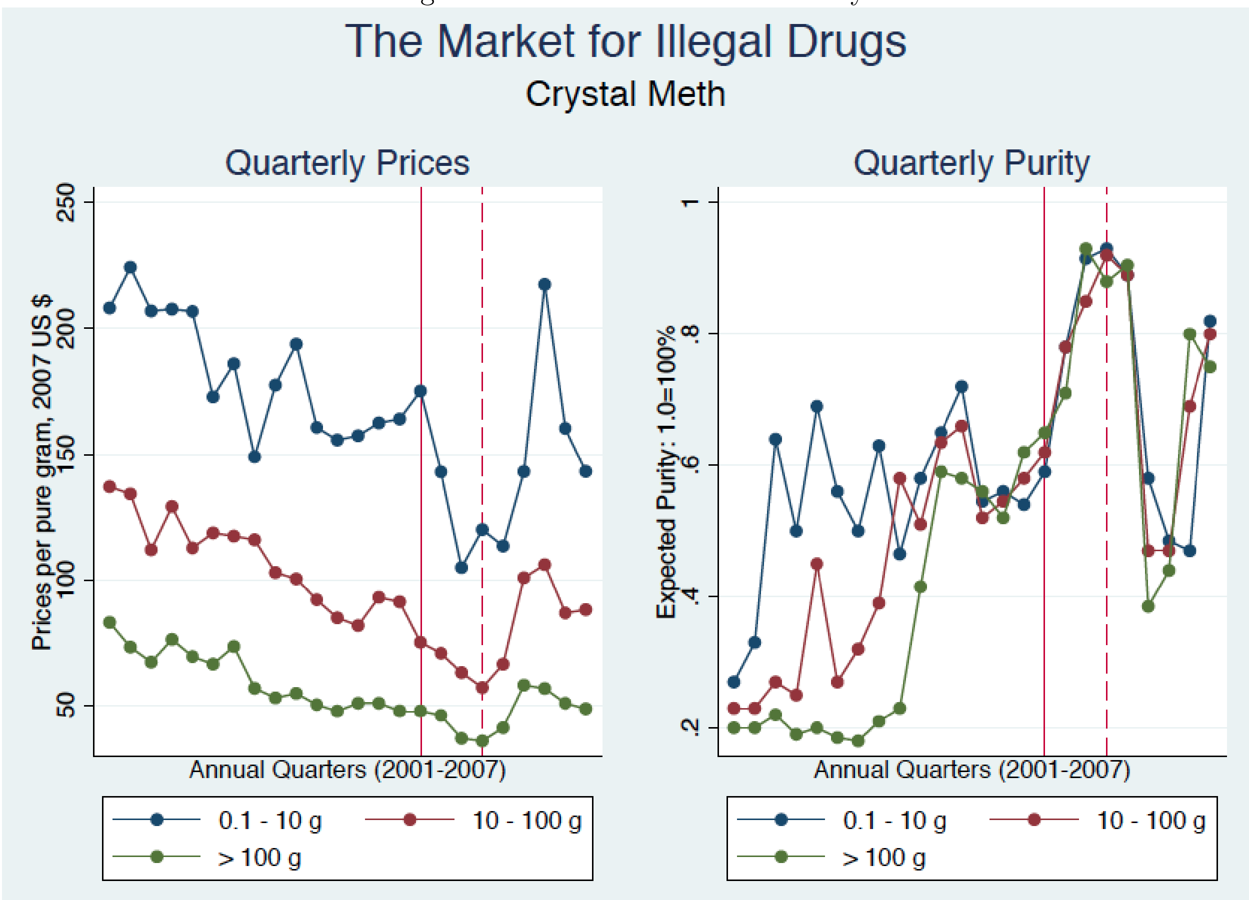
Figures

Figure 1: Map of U.S. State and Federal Restrictions Against Meth Chemical Precursors



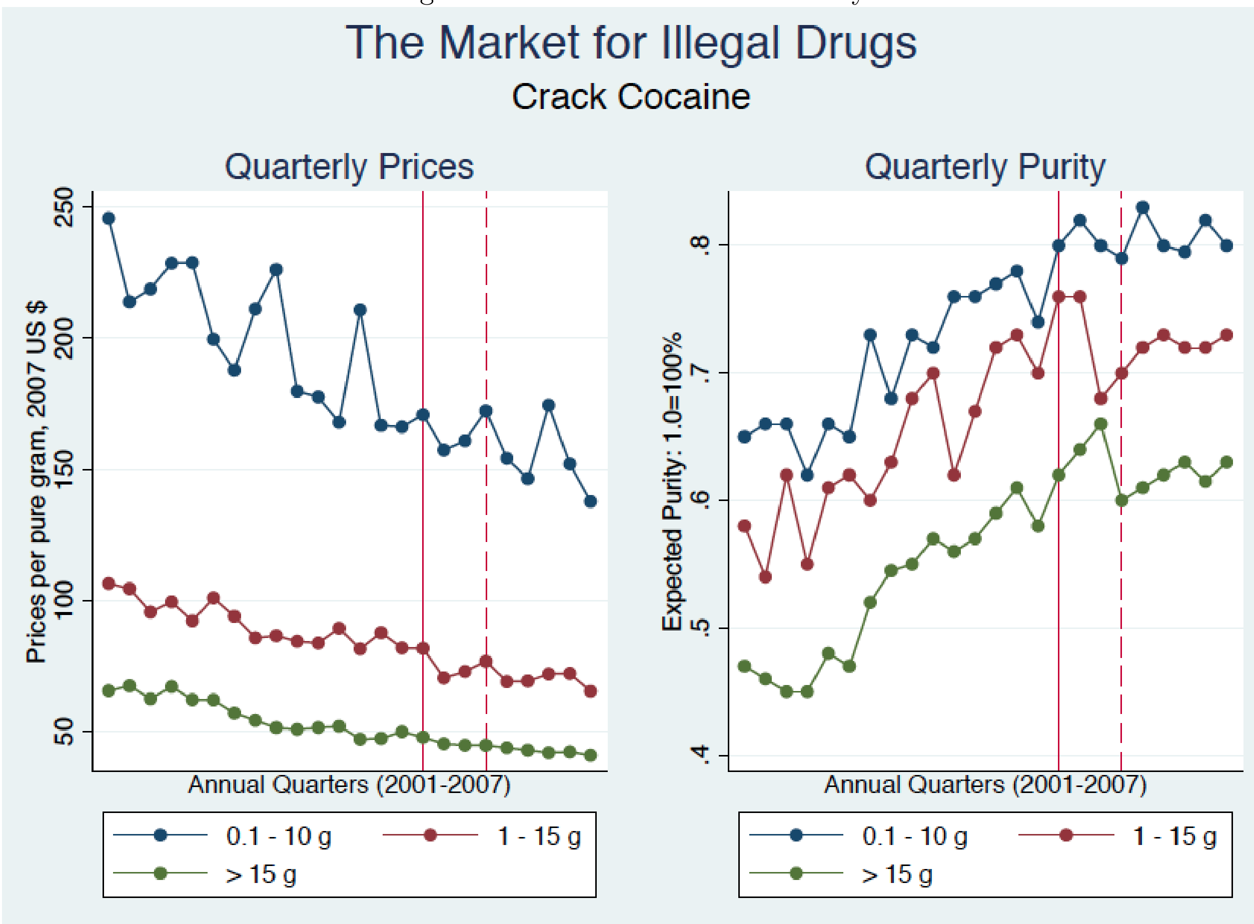
NOTES: This figure shows the year in which the first OTC restriction (either at the state or federal level) was enacted in each US State. Utah enacted a state regulation in 2001, followed by Oklahoma in 2004. The remaining states can be divided in three different groups: 1) Early adopters, implementing a state law in the year 2005, are: Alabama, Arizona, Arkansas, California, Colorado, Delaware, Florida, Georgia, Hawaii, Indiana, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Jersey, New Mexico, North Dakota, Oregon, Tennessee, Texas, Virginia, Washington, West Virginia, Wisconsin, Wyoming; 2) Late adopters, enacting a state-internal law mainly at the beginning of 2006, are: Idaho, Illinois, North Carolina, Ohio, South Carolina, South Dakota, Alaska, Maine and Vermont; 3) CMEA only adopters, adopting only the federal regulation the 30th of September of 2006, are: Connecticut, Maryland, Massachusetts, Nevada, New Hampshire, New York, Pennsylvania, Rhode Island. Alaska and Hawaii are omitted for illustrative purposes only. Both enacted a state law in 2005. Source (DEA, 2007)

Figure 2a - Market Prices and Purity



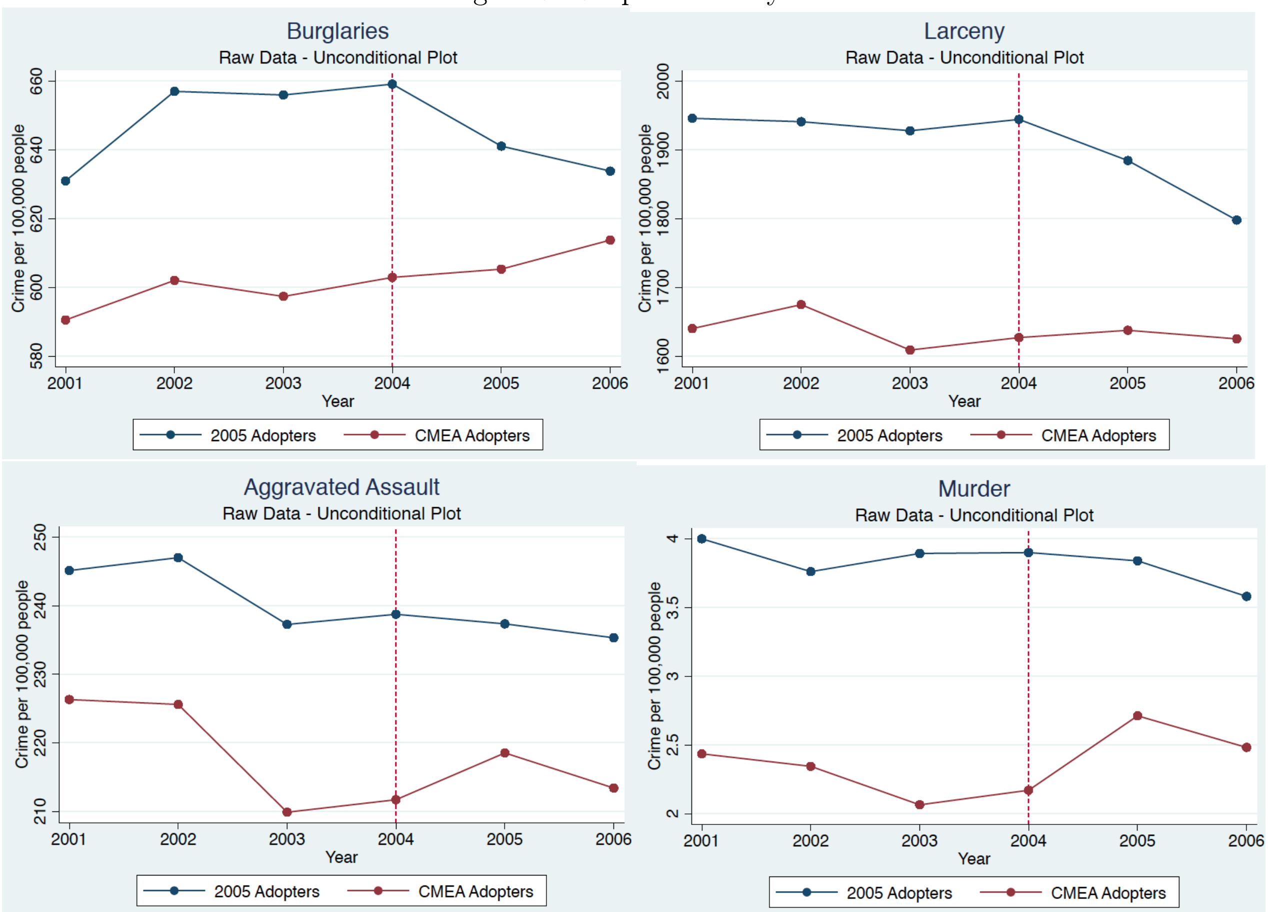
Notes: This figure shows the evolution of prices and estimated purities for crystal methamphetamines. Data are obtained from the public report "The Price and Purity of Illicit Drugs" (2008) of the Institute for Defense Analysis (IDA) for the Office of National Drug Control Policy (ONDCP). All price and purity estimates were derived from records in the STRIDE database maintained by the Drug Enforcement Administration (DEA). Data on prices and purity are expressed per pure gram of the substance for different weight categories, summarizing the different prices for different levels in the illegal-drug distribution chain. Prices are expressed in 2007 US dollars, are reported on a quarterly basis and are aggregated at the national level. The first vertical line represents the 4th quarter of 2004. The second vertical line represents the 3rd quarter of 2005. At this date 70% of early adopters states implemented an OTC restriction.

Figure 2b - Market Prices and Purity



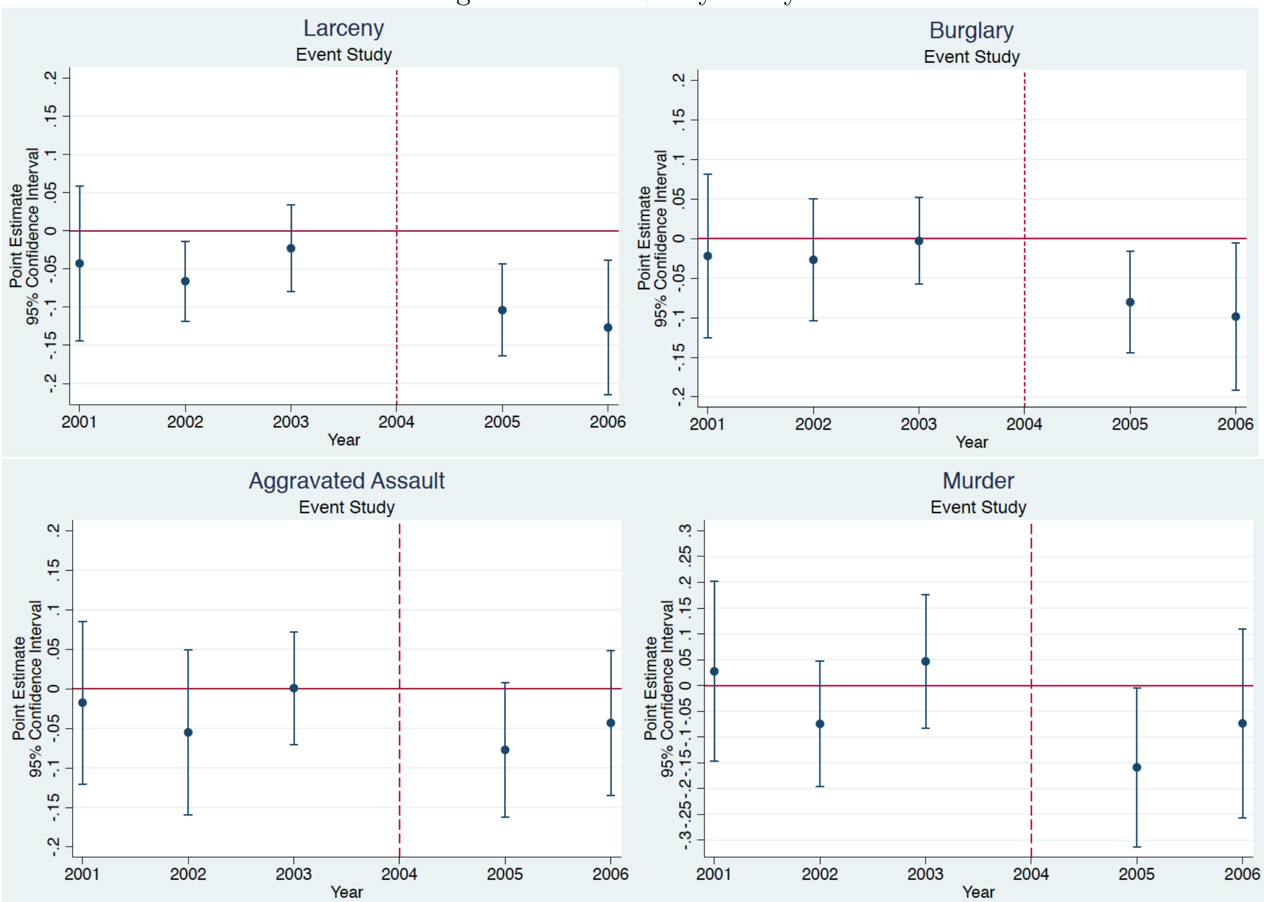
Notes: This figure shows the evolution of prices and estimated purities for crack cocaine. Data are obtained from the public report "The Price and Purity of Illicit Drugs" (2008) of the Institute for Defense Analysis (IDA) for the Office of National Drug Control Policy (ONDCP). All price and purity estimates were derived from records in the STRIDE database maintained by the Drug Enforcement Administration (DEA). Data on prices and purity are expressed per pure gram of the substance for different weight categories, summarizing the different prices for different levels in the illegal-drug distribution chain. Prices are expressed in 2007 US dollars, are reported on a quarterly basis and are aggregated at the national level. The first vertical line represents the 4th quarter of 2004. The second vertical line represents the 3rd quarter of 2005. At this date 70% of early adopters states implemented an OTC restriction.

Figure 3: Graphical Analysis



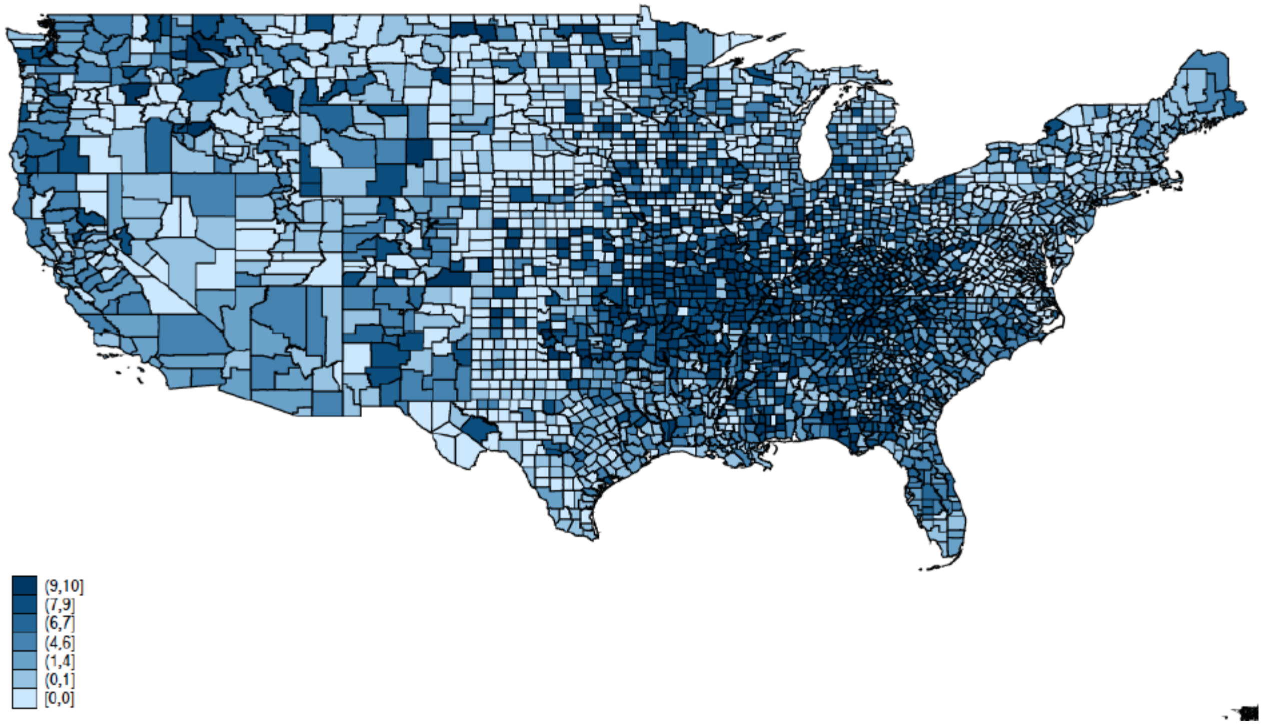
NOTES: This figure shows the evolution of larceny, burglary, aggravated assault and murder in states that adopted an internal regulation in 2005 ("2005 adopters") and in states where only the federal act CMEA was passed the 30th of September 2006 ("CMEA adopters"). For the case of murder I have excluded the counties belonging to New York city due to the 3000 victims of the 9/11 being recorded in the Murder category by the UCR. These counties are Queens, Richmond, New York, Kings and Bronx.

Figure 4: Event-Study Analysis



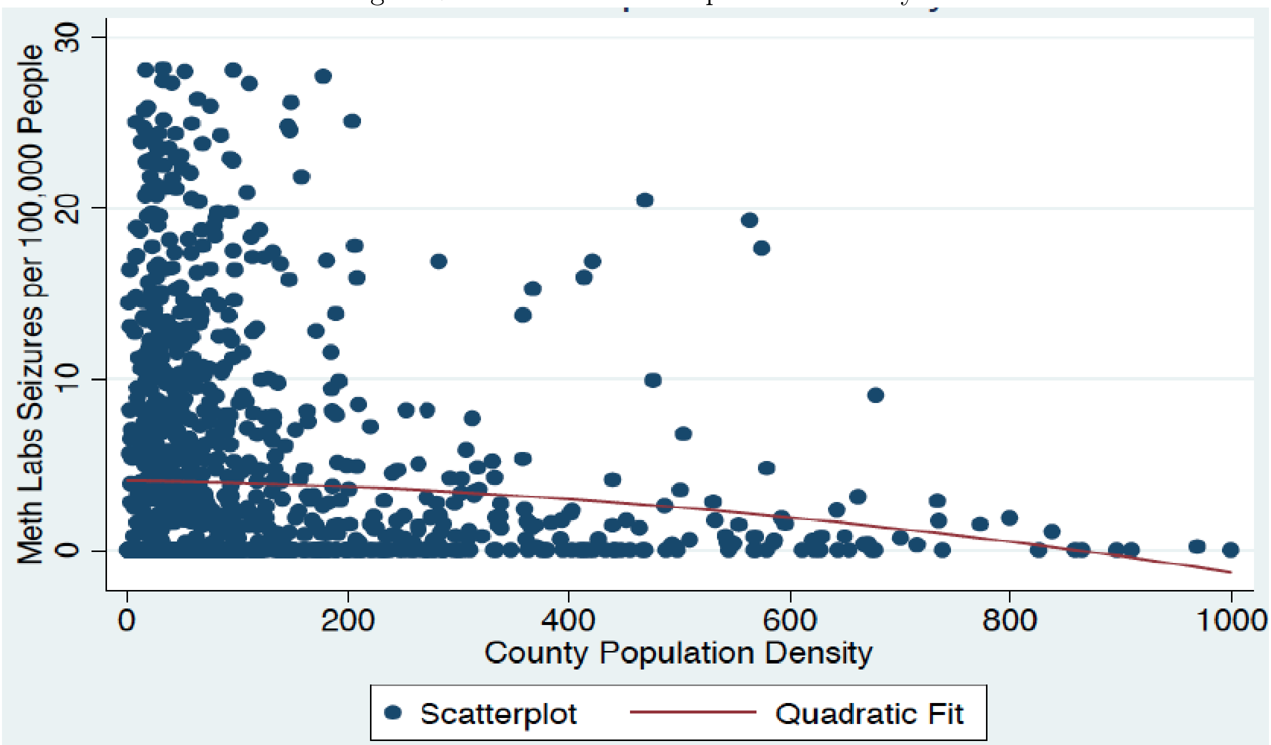
NOTES: This figure shows the plot of the coefficients obtained using the event study estimation as in equation (2) for burglary, larceny, assault and murder. Standard errors are clustered at the state level. The omitted category is the interaction between the two dummy variables "treated" and "year 2004". Confidence intervals at the 95% level are reported.

Figure 5: Map of Meth-Labs Seizures in 2004



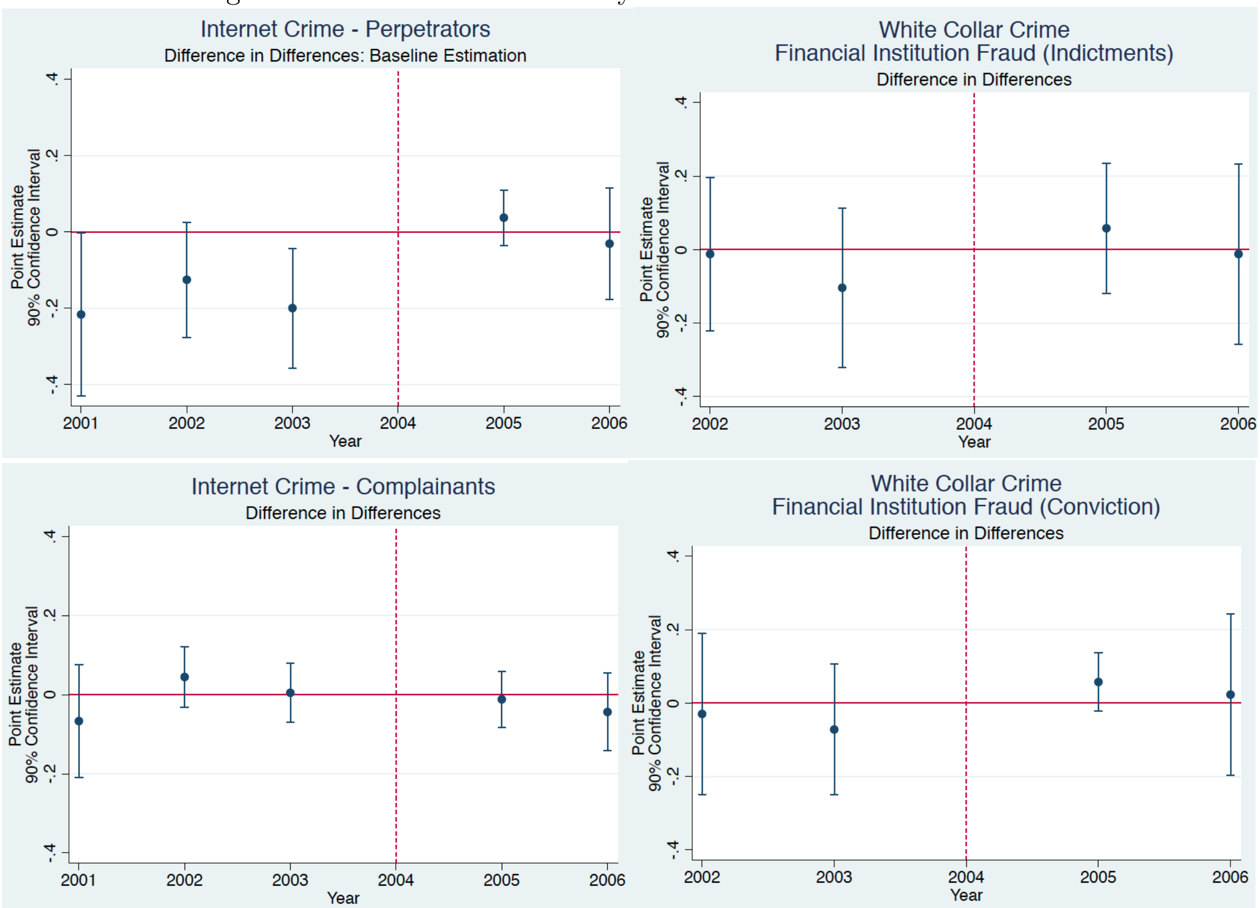
NOTES: This Figure shows the geographical distribution (expressed in deciles) of meth-labs seized by law enforcement agencies in 2004. Alaska and Hawaii are eliminated from the figure for illustrative purposes only. Source (DEA, 2012).

Figure 6: Meth-Labs and Population Density



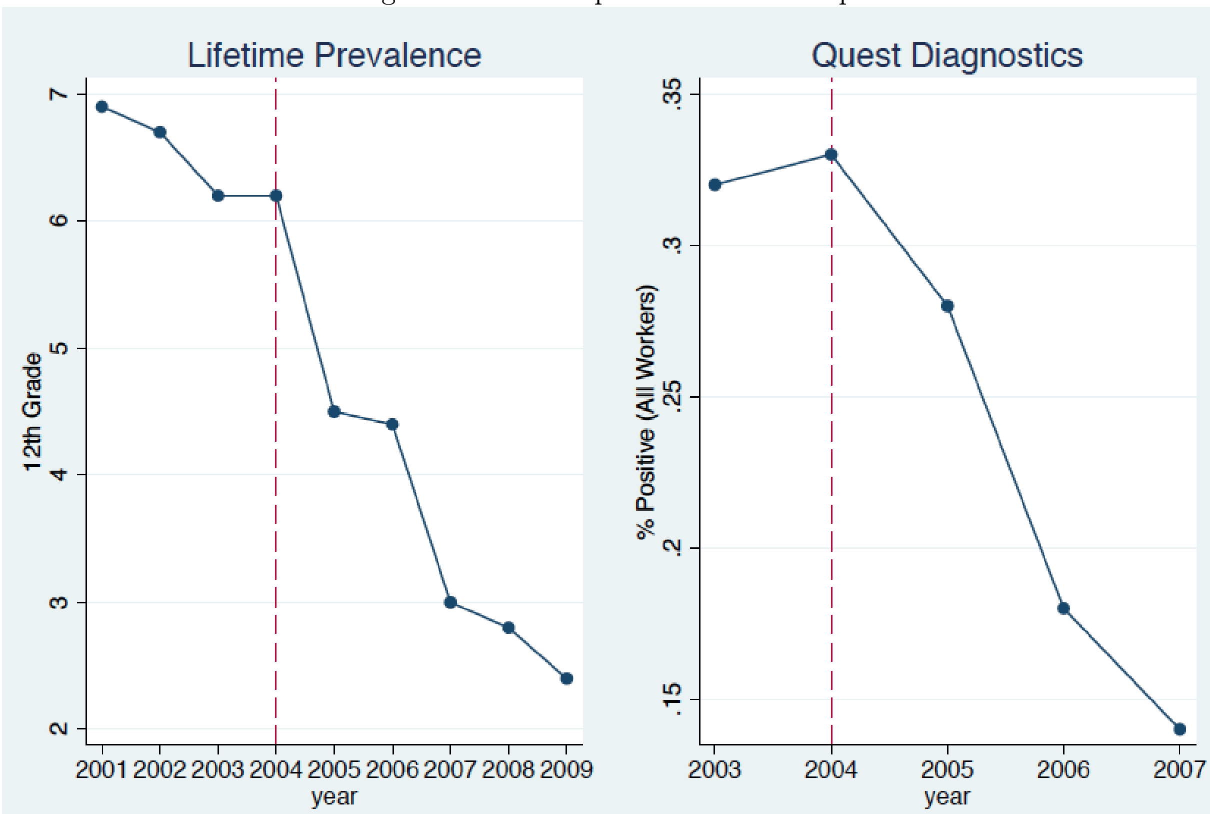
NOTES: This figure shows the scatterplot and the quadratic fit of the number ofmeth-labs seizured in 2004 in each county normalized per 100,000 people and the county population density in 2001. Both distributions are trimmed at the top 5% for illustrative purpose only.

Figure 7: Two Placebo Tests o Cybercrime and White-Collar Crime



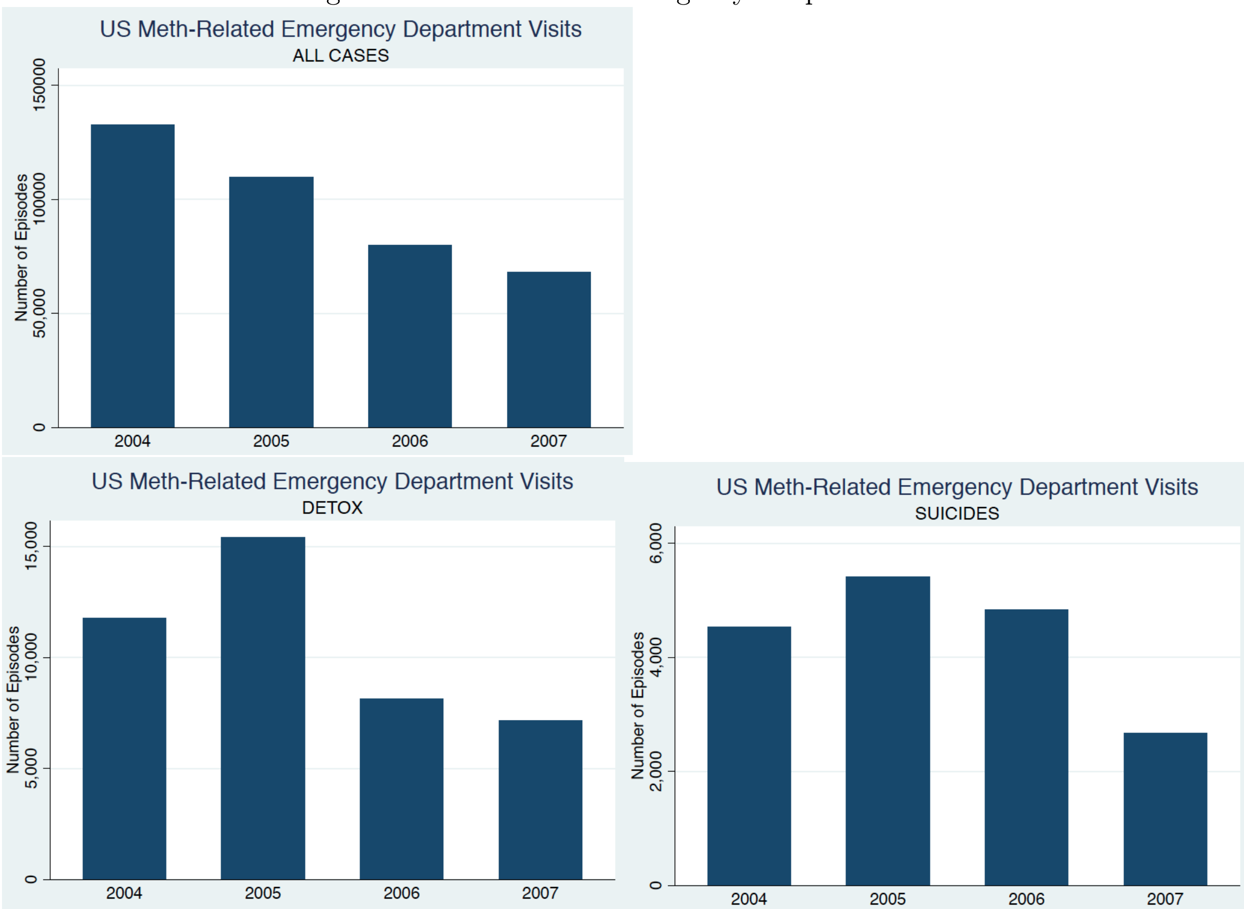
Notes: This figure shows a placebo test on Internet and financial crime using the event study estimation of equation (2) with mean of control variables collapsed at the state-year level. Standard errors are clustered at the state level. The omitted category is the interaction between the two dummy variables "treated" and "year 2004". Due to the placebo nature of this exercise, I plot more conservative 90% confidence intervals.

Figure 8 - Methamphetamine Consumption



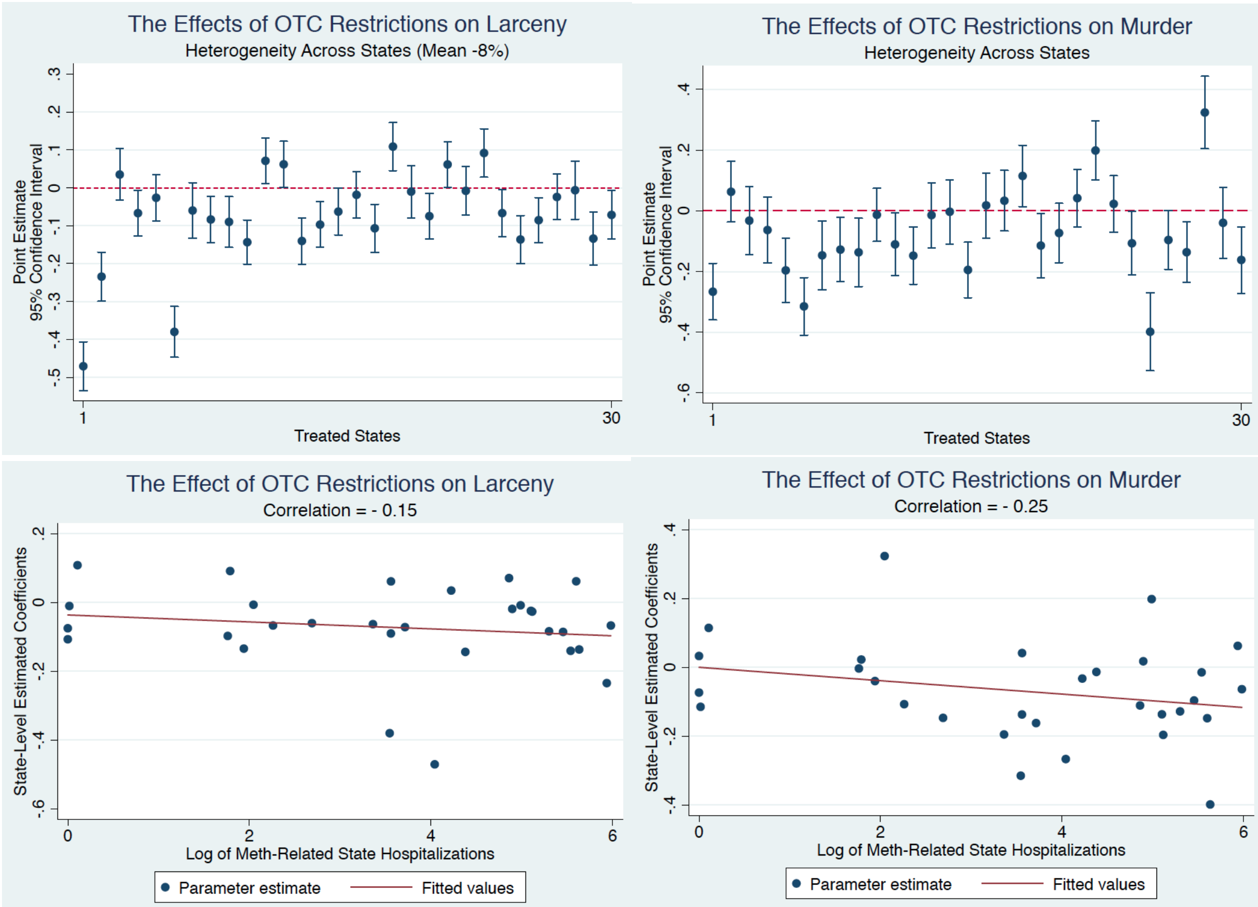
Notes: This figure shows the pattern of crystal meth consumption: lifetime prevalence (left-side) and work drug test (right-side). Sources: Monitoring the Future (University of Michigan) and Quest Diagnostics.

Figure 9: Meth-Related Emergency Hospitalizations



Notes: Source is the Drug Abuse Warning Network (DAWN). DAWN is a public health surveillance system that monitors drug-related emergency department (ED) visits in the United States and is a source for monitoring methamphetamine use. DAWN offers a unique perspective by examining use severe enough to warrant an ED visit. To be a DAWN case, the ED visit must have involved a drug, either as the direct cause of the visit or as a contributing factor.

Figure 10: Heterogeneity in the Impact of OTC Restrictions, by U.S. State



Notes: The top panel of this figure shows the plot of the 30 coefficients estimated using regression (7). The bottom panel correlates these coefficients with the state-level measure of meth-related hospitalizations in 2004.

Table I–A
Pre-Intervention Differences, Illegal Drugs Penetration

	(1) Control	(2) Treated	(3) Difference
Crystal-Meth			
Meth-labs Seizures	0.3	6.08	-5.77***
Meth-related Hospitalizations	20.43	66.88	-46.46***
Amphetamines-related Hospitalizations	4.92	21.79	-16.87***
Other dang. Non-narcotics (arrests possess.)	28	51.81	-23.82***
Other dangerous non narcotics (arrests sale)	7.09	18.28	-11.19***
Synthetics narcotics (arrests possession)	12.46	26.86	-14.40***
Synthetics narcotics (arrests sale)	4.84	12.95	-8.11***
Other Illegal Drugs			
Cocaine and Heroin (arrests possession)	93.18	59.31	33.87***
Cocaine and Heroin (arrests sale)	54.37	29.22	25.15***
Marijuana (arrests possession)	272.48	219.89	52.59***
Marijuana (arrests sale)	28.88	32.66	-3.78**
Alcohol Hospitalizations	753.01	399.96	353.05***
Cocaine Hospitalizations	446.3	149.98	296.32***
Marijuana Hospitalizations	359.84	240.85	118.99***
Heroin Hospitalizations	343.14	34.57	308.57***
Over the Counter Hospitalizations	1.69	1.46	0.24***

Notes: This table shows the pre-intervention mean (2001 to 2004 included) computed at the county level (arrests) and at the state level (hospitalization) in control states ("CMEA only", column 1) and treated states ("Early Adopters", column 2). Column 3 shows the t-test of the difference between column 1 and column 2. Arrests and hospitalizations are expressed per 100,000 people.

Table I–B
Pre-Intervention Differences, Criminal Activity

	(1) Control Counties	(2) Treated Counties	(3) Difference
Larceny	1637.81	1939.75	-301.94***
Burglary	478.22	650.81	-172.59***
Robbery	84.2	48.53	35.68***
Motor/Vehicle Theft	211.08	210.07	1.01
Murder	3.62	3.89	-0.27
Assault	228.37	242.02	-13.66
Rape	25.67	27.81	-2.13**
Arson	22.29	18.23	4.05***

Notes: This table shows the pre-intervention mean (2001 to 2004 included) computed at the county level in counties belonging to control states ("CMEA only", column 1) and county belonging to states that adopted a state regulation in 2005 ("Early Adopters", column 2). Column 3 shows the t-test of the difference between column 1 and column 2. Crimes are expressed per 100,000 people.

Table I–C
Pre-Intervention Differences, Socio-Economic Controls

	(1) Control Counties	(2) Treated Counties	(3) Difference
Banks & commercial deposits	34.56	40.27	-5.71***
Total deposits	1,686,258.58	1,266,475.58	419783***
People below the poverty line	18,547.59	19,236.64	-689.05***
Social security recipients	428.16	387.94	40.22***
Density	1,846.44	224.65	1621.79***
Unemployment %	5.07	5.74	-0.67***
Stand. Measure of poverty	0.1	0.14	-0.04***
Income per capital	32,072.9	25,477.1	6595.80***
Police	2.46	4.27	-1.80***
Police-Administrative	1.73	3.75	-2.02***

Notes: This table shows the pre-intervention mean (2001 to 2004 included) computed at the county level in counties belonging to control states ("CMEA only", column 1) and county belonging to states that adopted a state regulation in 2005 ("Early Adopters", column 2). Column 3 shows the t-test of the difference between column 1 and column 2. Variables are expressed per 100,000 people, when meaningful.

Table II-A: Difference in Differences
Baseline Estimation

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * Post	-0.0750**	-0.0720**	-0.0495	-0.131**
	(0.0387)	(0.0328)	(0.0522)	(0.0573)
Observations	9,687	9,687	9,687	9,687
R-squared	0.006	0.005	0.000	0.001
Number of counties	1,627	1,627	1,627	1,627
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. The estimating sample goes from 2001 to 2006 included. Year FE and county FE are included. Outcome variables are larceny, burglary, aggravated assault and murder. These are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. Treated*Post is the interaction of the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise).

Table II-B: Difference in Differences
Baseline Estimation

	(1) Robbery	(2) Arson	(3) Rape	(4) Vehicle Theft
Treated * Post	-0.0784	0.0449	-0.0830	-0.0114
	(0.0582)	(0.103)	(0.0873)	(0.0393)
Observations	9,687	9,687	9,687	9,687
R-squared	0.001	0.001	0.004	0.002
Number of counties	1,627	1,627	1,627	1,627
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. The estimating sample goes from 2001 to 2006 included. Year FE and county FE are included. Outcome variables are robbery, arson, aggravated assault and murder. These are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. Treated*Post is the interaction of the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise).

Table III: Robustness Check
Baseline Estimation + All County Observables

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * Post	-0.0818**	-0.0744**	-0.0406	-0.103**
	(0.0382)	(0.0317)	(0.0524)	(0.0527)
Observations	9,664	9,664	9,664	9,664
R-squared	0.009	0.007	0.003	0.005
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. The estimating sample goes from 2001 to 2006 included. Year FE and county FE are included. Outcome variables are larceny, burglary, aggravated assault and murder. These are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. Treated*Post is the interaction of the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise). I include the following county observables: income per capita, percentage of people below the poverty line, unemployment, social security recipients, average monthly payment per subsidy, commercial banks and saving institutions per 100,000 inhabitants, amount of banking and saving deposits, population density.

Table IV-A
Event study estimation

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	-0.0460	-0.0311	-0.0267	-0.0347
	(0.0501)	(0.0533)	(0.0513)	(0.0745)
Treated * 2002	-0.0660**	-0.0267	-0.0550	-0.0737
	(0.0267)	(0.0392)	(0.0531)	(0.0629)
Treated * 2003	-0.0229	-0.00283	0.00101	0.0475
	(0.0289)	(0.0280)	(0.0364)	(0.0660)
Treated * 2005	-0.104***	-0.0805**	-0.0775*	-0.160**
	(0.0308)	(0.0326)	(0.0434)	(0.0787)
Treated * 2006	-0.127***	-0.0987**	-0.0434	-0.0755
	(0.0448)	(0.0474)	(0.0469)	(0.0929)
Observations	9,664	9,664	9,664	9,664
R-squared	0.009	0.007	0.003	0.005
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I also include county FE, year FE and all county observables. Outcomes are larceny, burglary, assault and murder.

Table IV-B
Event study estimation

	(1) Robbery	(2) Rape	(3) Arson	(4) Vehicle Theft
Treated * 2001	0.101*	-0.0509	-0.0240	-0.0484
	(0.0583)	(0.0983)	(0.0758)	(0.0578)
Treated * 2002	0.0575	-0.0403	-0.0180	-0.0555
	(0.0685)	(0.0684)	(0.0725)	(0.0504)
Treated * 2003	0.0681	-0.104*	0.0735	-0.0319
	(0.0481)	(0.0606)	(0.0777)	(0.0400)
Treated * 2005	-0.0520	-0.144**	0.0530	-0.0463
	(0.0508)	(0.0761)	(0.113)	(0.0364)
Treated * 2006	-0.00849	-0.125	0.0697	-0.0647
	(0.0783)	(0.149)	(0.0923)	(0.0386)
Observations	9,664	9,664	9,664	9,664
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I also include county FE, year FE and all county observables. Outcomes are robbery, rape, arson and vehicle theft.

Table V-A: Robustness
Baseline + Police

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	-0.0426	-0.0300	-0.0244	-0.0353
	(0.0495)	(0.0525)	(0.0514)	(0.0744)
Treated * 2002	-0.0625**	-0.0255	-0.0527	-0.0744
	(0.0260)	(0.0386)	(0.0530)	(0.0627)
Treated * 2003	-0.0202	-0.00197	0.00243	0.0474
	(0.0286)	(0.0276)	(0.0362)	(0.0661)
Treated * 2005	-0.102***	-0.0798**	-0.0768*	-0.159*
	(0.0306)	(0.0325)	(0.0445)	(0.0790)
Treated * 2006	-0.128***	-0.0991**	-0.0445	-0.0748
	(0.0450)	(0.0479)	(0.0474)	(0.0930)
Observations	9,664	9,664	9,664	9,664
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I also include county FE, year FE, all county observables and police officers with arrests powers and with administrative duties. Outcomes are larceny, burglary, assault and murder.

Table V-B Robustness
Baseline + States' Specific Linear Trends

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2002	-0.0348	-0.00563	-0.0363	-0.0508
	(0.0260)	(0.0225)	(0.0479)	(0.0578)
Treated * 2003	-0.00829	0.00658	0.0104	0.0583
	(0.0286)	(0.0195)	(0.0294)	(0.0571)
Treated * 2005	-0.119***	-0.0894**	-0.0863*	-0.172*
	(0.0361)	(0.0412)	(0.0435)	(0.0981)
Treated * 2006	-0.159***	-0.121	-0.0649	-0.0971
	(0.0582)	(0.0726)	(0.0636)	(0.132)
Observations	9,664	9,664	9,664	9,664
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I also include county FE, year FE, all county observables and states' specific linear trends. Outcomes are larceny, burglary, assault and murder.

Table V-C: Robustness
Baseline Weighted By FBI Coverage Indicator

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	-0.0435	-0.0281	-0.0283	-0.0393
	(0.0500)	(0.0529)	(0.0508)	(0.0752)
Treated * 2002	-0.0630**	-0.0248	-0.0559	-0.0749
	(0.0261)	(0.0387)	(0.0525)	(0.0630)
Treated * 2003	-0.0215	-0.00169	-0.000712	0.0488
	(0.0282)	(0.0276)	(0.0360)	(0.0664)
Treated * 2005	-0.0969***	-0.0756**	-0.0748*	-0.160*
	(0.0288)	(0.0313)	(0.0413)	(0.0795)
Treated * 2006	-0.122***	-0.0940*	-0.0426	-0.0783
	(0.0448)	(0.0477)	(0.0469)	(0.0939)
Observations	9,664	9,664	9,664	9,664
Number of Counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I also include county FE, year FE and all county observables. Outcomes are larceny, burglary, assault and murder. I weight the regression using the FBI Coverage indicator, a measure of the reliability on the information for crime in each county/year.

Table V-D: Robustness
Linear Measure of Crime

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	3.126	-15.75	-8.901	-1.655*
	(50.11)	(22.15)	(9.316)	(0.847)
Treated * 2002	-35.80	0.308	-6.999	-0.350
	(32.90)	(17.04)	(11.26)	(0.305)
Treated * 2003	16.23	4.144	0.163	0.0475
	(28.57)	(10.73)	(5.419)	(0.258)
Treated * 2005	-88.02***	-22.94*	-10.22*	-0.597*
	(27.01)	(13.77)	(5.596)	(0.349)
Treated * 2006	-176.6***	-37.35	-4.329	-0.478
	(48.80)	(23.61)	(7.616)	(0.333)
Observations	9,664	9,664	9,664	9,664
Number of Counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed per 100,000 people I also include county FE, year FE and all county observables. Outcomes are larceny, burglary, assault and murder.

Table V-E: Robustness
Fixed Effects Poisson Estimation

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	-0.00238	-0.0151	-0.0422	-0.416***
	(0.0193)	(0.0242)	(0.0307)	(0.152)
Treated * 2002	-0.0243*	0.00181	-0.0346	-0.0964
	(0.0135)	(0.0204)	(0.0311)	(0.0735)
Treated * 2003	0.00878	0.00940	0.000143	0.0149
	(0.0103)	(0.0168)	(0.0212)	(0.0815)
Treated * 2005	-0.0481***	-0.0368*	-0.0460**	-0.178**
	(0.0103)	(0.0199)	(0.0203)	(0.0809)
Treated * 2006	-0.0913***	-0.0628***	-0.0210	-0.160**
	(0.0138)	(0.0230)	(0.0269)	(0.0800)
Observations	9,648	9,648	9,648	9,009
Counties	1,619	1,619	1,619	1,511
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Obs.	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. I also include county FE, year FE and all county observables. Outcomes are larceny, burglary, assault and murder. I use a fixed effects Poisson regression with the count number of crimes as outcome variable.

Table VI
Circumstances Leading to a Murder

Type of Crime	Frequency	Percent
Theft-Related		
Robbery	6,747	6.61
Burglary	567	0.56
Larceny	103	0.1
Motor vehicle theft	160	0.16
Sex-Related		
Rape	287	0.28
Prostitution and commercialized vice	67	0.07
Other sex offense	76	0.07
Lovers triangle	722	0.71
Gangs & Drug Trafficking Related		
Narcotic drug laws	4,189	4.1
Gangland killings	614	0.6
Juvenile gang killings	5,454	5.34
Violent Altercations		
Brawl due to influence of alcohol	892	0.87
Brawl due to influence of narcotics	535	0.52
Argument over money or property	1,357	1.33
Other arguments	24,871	24.35
Related to Negligence		
Gun-cleaning death - other than self	9	0.01
Children playing with gun	127	0.12
Other negligent handling of gun	328	0.32
All other manslaughter by negligence	612	0.6

Note: This table reports the number and relative frequency of homicides divided by specific circumstances under which these occurred. Source NAJCD 2001-2006.

Table VII: Difference in Differences
Homicides Circumstances

	(1) Theft	(2) Sex	(3) Violent Altercations	(4) Negligence	(5) Gangs and Systemic Violence
Treated * 2001	0.0440**	0.0200	-0.0798**	0.00172	-0.048
	(0.0193)	(0.0228)	(0.0353)	(0.0125)	(0.039)
Treated * 2002	0.000848	0.0293*	0.00611	-0.0163	0.012
	(0.0251)	(0.0145)	(0.0406)	(0.0151)	(0.07)
Treated * 2003	0.0442*	0.0192	-0.00562	0.0115	-0.004
	(0.0221)	(0.0223)	(0.0620)	(0.0133)	(0.011)
Treated * 2005	0.00424	0.0124	**-0.0822****	0.0102	-0.007
	(0.0200)	(0.0171)	**(0.0383)**	(0.0130)	(0.01)
Treated * 2006	-0.0334	0.000436	0.0167	-0.00411	0.002
	(0.0308)	(0.0142)	(0.0280)	(0.00811)	(0.01)
Observations	9,664	9,664	9,664	9,664	9,664
Counties	1,625	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
County Observables	YES	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. I use estimating equation (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I also include county FE, year FE and all county observables. Outcomes are homicides in the following circumstances: gangs-related homicide, theft, sex, violent altercation and negligence.

Table VIII: Triple Difference in Differences
Population Density

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * Post	-0.0861**	-0.0898***	-0.0560	-0.129**
	(0.0397)	(0.0319)	(0.0534)	(0.0540)
Treated * Post* Density	0.00304	0.0179**	0.0148*	0.0394***
	(0.00469)	(0.00838)	(0.00844)	(0.00794)
Observations	9,585	9,585	9,585	9,585
Number of counties	1,605	1,605	1,605	1,605
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. The estimating sample goes from 2001 to 2006 included. Year FE, county FE and all county observables are included. Outcome variables are larceny, burglary, aggravated assault and murder. These are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. Treated*Post is the interaction of the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise). Density is obtained as the ratio of land area divided by county population in 2001. The interaction Post*Density is included in all the specifications.

Table IX: Triple Difference in Differences
Meth-Labs Seizures in a County, Pre-Reform

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * Post	-0.0846**	-0.0781**	-0.0300	-0.0804
	(0.0398)	(0.0351)	(0.0561)	(0.0624)
Treated * Post * Labs	-0.0132**	-0.00888	-0.0382**	-0.0482
	(0.00646)	(0.0107)	(0.0179)	(0.0438)
Observations	9,646	9,646	9,646	9,646
Number of counties	1,618	1,618	1,618	1,618
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. The estimating sample goes from 2001 to 2006 included. Year FE, county FE and all county observables are included. Outcome variables are larceny, burglary, aggravated assault and murder. These are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. Treated*Post is the interaction of the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise). Labs is the number of meth-labs seizures in the county in 2004. The interaction Post*Labs is included in all the specifications.

Table X
TEDS Hospitalizations

	(1) Meth	(2) Alcohol	(3) Heroin	(4) Cocaine	(5) Marijuana	(6) Amphetamines
Treated * Post	**0.341****	0.0317	0.000987	-0.0118	0.0669	-0.0555
	(0.160)	(0.0409)	(0.0863)	(0.0900)	(0.0475)	(0.187)
Observations	224	224	224	224	224	224
Number of states	38	38	38	38	38	38
Year FE	YES	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES	YES
State Observables	YES	YES	YES	YES	YES	YES

Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the State level. The level of observation is state – year. This table reports the results of a difference in differences specification for hospitalizations due to: meth, alcohol, heroin, cocaine, marijuana, and amphetamines. The sample goes from 2001 to 2006 included. Treated*Post is the interaction of the variable treated (a dummy taking the value of 1 if the state has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise).