Drugs and Crime in the US: Evidence from OTC Regulations Targeting Crystal-Meth Precursors Chemicals

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This paper investigates the effects of the market for illegal drugs on crime. I focus on crystal methamphetamines, using as a source of exogenous variation OTC restrictions to critical inputs of production. Several DD and IV designs are performed on a newly assembled panel dataset, unveiling the interlinkages between drugs and criminal activity due to a unique combination of DEA and FBI county-level information. I show that OTC restrictions led to a decline of 8% to 16% in both property and violent crimes. I explore the underlying mechanisms detecting: 1) 37% reduction in operating meth labs, 2) 23% drop in the arrests for sale, 3) a short-term spike in methamphetamines' prices, 4) an elasticity of crime to meth-labs in the range of 0.2 – 0.3. I further reconcile the findings with the atypical segmentation of this retail market and with ethnographic/medical evidence suggesting that OTC restriction put a cap on meth-epidemic, curbing the spiral of heavy drugs' abuse and associated criminal behavior.

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I. Introduction

The market for illegal drugs – in its main components of production, distribution and consumption of illegal substances – generates an annual economic loss for the United States estimated around $200 billion (ONDCP, 2007). This value reflects lost productivity, environmental destruction, healthcare expenditures and crime, with almost 50% of US prison inmates being clinically addicted to some illicit substance (NACDD, 2014).

In particular, the expansion of this clandestine market might exacerbate criminal activity via three major channels: *economic*, due to users' need to support drug-habits or due to their inability to work, typically resulting in the proliferation of theft crimes; *systemic*, due to the production and trafficking of the drug itself, exemplified by gangs' violence in the streets to gain control over the territory and *pharmacological*, due to the psychosis associated with immediate or chronic drugs' effects, leading to any form of physical and sexual violence (Goldstein, 1985).

More indirectly, the relocation of police effort and public resources – aimed at containing the growth of this dangerous market via deterrence or incapacitation mechanisms – might lead to unintended consequences if criminals specialize in different illegal activities characterized by lower probability of detection, or if convicts' likelihood of reoffending is influenced by detrimental peer effects in severely overcrowded prisons.

Nonetheless, while detecting and quantifying these channels is critical to implement cost-effective policy interventions that – by antagonizing in the first place the expansion of these dangerous markets might also reduce the proliferation of crime – assessing the existence and empirical relevance of these effects has proven difficult.

Two main obstacles have hindered such an analysis. First, markets for illegal drugs are not as good as randomly assigned, but are rather endogenously located, following existing economic trends or cross-sectional area characteristics. Secondly, these markets – in their major components of production, distribution and consumption of illegal substances – are difficult to measure, mainly because of their intrinsic concealed nature.

This paper contributes to the existing literature on the determinants of crime by focusing on crystal methamphetamine: a highly addictive, neurotoxic synthetic substance, considered by almost 60% of local law-enforcement agencies as the most dangerous illicit drug in the United States, due to its alleged role in generating thefts, violence and sex offenses (NACO, 2005).

I use as a source of exogenous variation a shock to domestic production, caused by the enactment of states and federal interventions restricting the access to methamphetamines' critical chemical inputs of production: ephedrine or pseudoephedrine. These chemicals are contained in cold medicines that – prior to these restrictions – were easy to obtain from pharmacies and local shop and were used, alongside with other legal products readily available to the public, to synthesize methamphetamines in clandestine – highly dangerous – laboratories.

I implement several quasi-random empirical designs on a newly assembled county-level panel dataset. Most importantly, this dataset provides an exclusive look at the interconnections between market for illegal drugs and criminal activity. Specifically, it combines DEA detailed information on location and number of clandestine meth-labs, prices and purity of methamphetamines and other illegal substances, to FBI data on property and violent crimes, circumstances surrounding homicides, hate-crimes, arrests for possession and sale of a variety of drugs, states and federal legislation regulating the access to methamphetamines' precursors, hospitalizations from methamphetamines' abuse and a wide set of socio-economic controls, obtained from a variety of other sources.

I start the empirical analysis using a DD design. I compare differences in crime between counties belonging to 1) states implementing OTC restrictions in 2005, due to a great prevalence of crystal methamphetamines production within their territory and 2) states characterized by higher predominance of other dangerous substances such as crack-cocaine and heroin, which did not implement any internal law to restrict the access to methamphetamines' chemical inputs. Given that the Combat Methamphetamines Epidemic *Federal* Act (CMEA) was implemented nationwide in the final part of 2006, I limit this analysis to the six years period 2001 – 2006.

While significant differences in pre-existing levels of illegal drugs penetrations explain the endogenous take up of OTC restriction in some US states, the validity of this DD design relies on the critical identifying assumption of conditional parallel trends. The graphical analysis of crime pre-trends supports the validity of this assumption, showing a smooth pre-intervention pattern in both property and violent crimes, as well as a post-regulation sharp decline in crime, only concentrated in treated states.

The DD specification, mirroring the evidence obtained from the graphical investigation, reveals a significant drop of burglaries, larcenies, aggravated assaults and murders in the range of 8% to 15% between 2006 and 2006. The estimates are robust across several specification such as the inclusion of county FE, a wide range of socio-economic controls, state-specific linear and quadratic trends, the weighting of the regressions by a measure of the quality of the information on reported crimes and the exclusion from the sample states sharing the borders with Mexico, the biggest exporter of methamphetamines in the US via Mexican drugs cartels.

I then devote the central part of the paper to explore potential mechanisms behind these findings.

To this end, I first examine the efficacy of OTC restrictions in disrupting the domestic production of crystal methamphetamines, including DEA data on meth-labs seized by law enforcement agencies, which will serve the analysis as a measure of the underlying clandestine domestic production within a county. My findings reveal that OTC restrictions decreased by 37% the number of methamphetamines labs seized by law enforcement agencies, with these estimates – arguably – representing a lower bound of the real reduction in the number of operating meth-labs.

The exit from the market of numerous low and medium meth-producers might have reduced the level of competition in the streets, hence lowering the systemic violence associated with drug trafficking. This hypothesis is tested using FBI data on drugs-related arrests and on the detailed circumstances under which homicides occurred. While I detect a significant 23% reduction in the arrests for sale of "other dangerous non-narcotics", the FBI category of illegal substances including crystal methamphetamines, no significant change is detected homicides related to drug trafficking and gangs violence.

I then shift my focus on examining the effects in the demand-side of the market and the possible interlinkages with the reduction in crime. Time series data on methamphetamines prices reveal that in the quarter where 70% of states enacted OTC restrictions, the price for 1 gram of pure methamphetamines raised by 55% to 108%, hitting the pick for lower quantities of the substance hence – plausibly – affecting the consumption of the substance. Importantly, despite the impossibility of performing a DD analysis due to the national level of aggregation of these data, the time series analysis for heroin, marijuana, crack-cocaine and powdered cocaine does not reveal any noticeable pick within the same time window.

This evidence seems to suggest that the rise in prices, while short-lived and possibly compensated by an intake in the US of methamphetamines via Mexican cartels, might have played a role in the reduction of criminal activity.

A deeper investigation of the qualitative features of the retail market specifically connected with domestic production – supported by FBI reports and surveys of arrestees – gives further insights on this theme. In particular, the ease in manufacturing crystal meth – alongside the strong addictive power of this substance – pushed a myriad of meth abusers to start their own domestic production, facing the risk of heavier criminal convictions mainly to sustain their own drug habit. This dynamic – particularly acute in rural areas of the county – generated a lack of specialization across different roles in the clandestine distributional chains, creating a segmented market where networks of abusers-producers where selling meth to a close network of family and acquaintances –

usually sharing a high level of addiction with all the relative consequences – rather than to strangers in the streets.

Ethnographic evidence suggests that the segmentation of the market, alongside the sudden increase in prices and the difficulty to find the substance outside the close network of acquaintances, might have curbed the immoderate consumption within networks of extreme abusers that – conceivably – where characterized by a high propensity to generate both property crimes, (to sustain the drug habit or to finance the illegal production), and violent crimes, (mainly deriving from the psychosis due to intense abuse).

I then move the analysis forward, exploiting the unique disaggregation of my data to quantify the overall causal effects of domestic production of methamphetamines on crime. To this end, I use a combination of DD and IV design. I exploit in the first-stage regression the quasi-random variation provided by OTC restrictions to predict the number of methamphetamine labs within a county. I then estimate the effects of meth-labs on criminal activity using two stages least square estimator. First stage and reduced form regressions are highly significant and have negative signs as expected. The F-statistic on the excluded instrument has a value of 104.7, noticeably reducing the concerns arising from the weak instrument bias. IV estimates reveal that a 10% increase in the number of meth-labs in a county leads to a significant increase of 2% to 4% in the number of larcenies, burglaries, aggravated assaults, murders and rapes in the same county.

I further investigate the links between drugs and violence, exploring FBI data on the detailed circumstances under which homicides occurred and on hate crimes, violent episodes motivated by any sort of religious, ethnic, racial and sexual bias against the victim. I show that OTC restrictions decreased by 8% the number of murders due to brawls and violent altercations, with no effect detected on homicides due to theft, sex and negligence. I also detect a more controversial increase in hate crimes, reconciling this evidence with FBI psychiatric reports stating that more than 60% of episodes of hate are caused by the desire of the "thrill or excitement of the moment" and the existence of a possible substitution effect between drugs abuse and violent behavior. Once again, this evidence seems to suggest that the main operating channel between OTC restrictions and crime is a drop in the extreme abuse of the substance.

The analysis approaches to a conclusion with the investigation of possible unintended consequences associated with the implementation of OTC restrictions. The lack of any effect on arrests for sales or possession of marijuana, cocaine and heroine – as well on prices and purities of these illegal drugs – while serving the purpose of being a sensible falsification test for this empirical analysis – suggests that the market for illicit drugs did not significantly shift towards the trafficking or the consumption of other illicit substances. Moreover, a spatial analysis focused on untreated counties sharing the borders with treated states, does not reveal significant relocation effects on meth-production and on criminal activity, even if the magnitude of the coefficients associated with murder might serve as a warning for policy makers.

This work has in fact the power to inform policy: policymakers should take into account the extra benefit deriving from the short-term reduction in crime, when contemplating cost and benefits of measures designed to disrupt the domestic production of methamphetamines. Nevertheless, this study also suggests the need of carefully considering the demand side of the market, with a particular focus on communities where the abuse of the illegal substance is extremely acute.

My findings contribute to several strands of the literature. First, this paper offers a systematic empirical investigation on the effects of the market for illegal drugs on crime. In particular, while earlier studies have addressed this issue using time-series and fixed effects frameworks, I exploit a sharp quasi-natural experiment and a newly built county-level dataset, using as exogenous variation OTC restrictions targeting methamphetamines' main chemical precursors.[1]

My study is hence closely related to a very recent literature that focuses on how drugs-policy intervention affects crime, through an increase or a relocation of police enforcement. In particular, Melissa Dell (2012) uses a regression discontinuity design to show that drug-related violence increases substantially after close elections of National Action Party (PAN) mayors. Her findings suggest that this violence is caused by rival traffickers' attempts to usurp territories after police crackdowns – linked to PAN aggressive policy – have weakened incumbent criminals. In a similar fashion, Adda, Mcconnel and Rasul (2014) show that cannabis depenalization policy in the London borough of Lambeth caused police to reallocate effort toward non-drug crime, leading to a significant reduction of all these type of felonies.

This paper also complements two other works on the market for methamphetamines. The first, by Dobkin and Nicosia (2009), estimates the effects of a different government effort aimed at reducing the supply of this substance in California in the year 1995.[2] While showing that methamphetamine price tripled, purity declined from 90 percent to 20 percent, amphetamine related hospital and treatment admissions dropped 50 percent and 35 percent, they do not find

[1] One of the first pioneering analysis in this area, Corman and Mocan (2000) show that drug usage in New York City has only a small effect on some property crimes. Nevertheless, the exclusive focus on the time series dimension coupled with the absence of a clean identification strategy might represent a potential limit of this work. Along these lines is the work of De Mello (2011). He investigates the effects on crime of crack-cocaine arrests in Sao Paolo using a fixed-effects framework. His empirical exercise, which relies on within province changes in the proportion of crack-cocaine arrests, show that these explains 30% of the time series variation in the homicides in the state of Sao Paolo.

[2] The Domestic Chemical Diversion Control Act (DCDCA) removed the record-keeping and reporting exemption for distributors of single-entity ephedrine products and empowered the DEA to deny or revoke a distributor's registration without proof of criminal intent. In May 1995, the DEA shut down two suppliers that appear to have been providing more than 50 percent of the precursors used nationally to produce methamphetamine. This is probably the largest "supply" shock that has occurred in any illegal drug market in the United States and was made possible by the substantial concentration in the supply of methamphetamine precursors (Dobkin and Nicosia, 2009).

substantial reductions in property or violent crime. The second study, by Dobkin, Nicosia and Weinberg (2014), focuses on the same OTC regulations explored in this paper, using a wide set of rich administrative datasets to detect the effects on the methamphetamines' market. Consistently with my results, they detect a 36% decrease in meth-labs seized by police. While my study benefits of the richness of their administrative information to get important insights on this clandestine market, I look at the effects of OTC restrictions from a different angle, assembling a unique county-level dataset matching DEA and FBI information, to unveil the causal impact of crystal methamphetamines on crime.

Finally, my paper adds to the very scarce literature on the determinants of hate crimes. In his seminal contribution, Becker (1968) considered criminal behavior using an economic framework of rational behavior in which agents maximize utility by performing a cost-benefits analysis. In this model, harm or loss to the individual is considered an externality, essentially an unintentional side effect of the offender's actions. In the case of a hate crime, however, it has been suggested that the loss of the victim is the primary reason for the offender's decision of committing the crime (Gale, Heath, and Ressler, 2002; Craig, 2002). The presumed irrationality of hate crimes could hence be explained by several factors that alter individual's preferences. Along these lines, Machin et Hanes (2014) find significant increases in hate crimes against Asians and Arabs that occurred almost immediately in the wake of London and New York error attacks. They hypothesize that attitudinal changes resulting from media coverage may act as an underlying driver of the spike in hate crimes.

In my study I propose an alternative link between hate-crimes and drug's abuse, showing a controversial increase in hate-violence and reconciling these findings with the possible existence of a substitution effects between meth-consumption and – seemingly irrational – violent behavior.

This paper unfolds as follows: section II provides background information on methamphetamine effects, production and precursors' legislation; section III presents all the datasets used in the analysis, providing relative summary statistics; section IV reports the reduced-form results aimed at detecting the effects of OTC restrictions on crime; section V explores the mechanisms; section VI reports other results; section VII concludes.

II. Institutional Background

This section aims to provide a comprehensive institutional background on the market for crystal methamphetamines. To this end, I first describe the effects associated with meth abuse. Then, I focus on the details concerning domestic production. Finally, I examine states and federal legislations restricting the access methamphetamines' critical precursors.

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 $20-25 for ¼ of grams. 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 orally to produce a release of high levels of dopamine and neurotransmitters into the brain, generating sensations of self-confidence, energy, alertness, pleasure, and sexual arousal. The high or "rush" from methamphetamine lasts from 8 to 24 hours while, in comparison, the high from cocaine lasts from 30 minutes to one hour.

With repeated use, meth exhausts accumulations of dopamine in the brain, simultaneously destroying the wiring of dopamine receptors.[3] This process is what makes crystal meth extremely addictive, leading frequent users towards the physical impossibility of experiencing pleasure, (a condition known as *anhedonia*), and the consequent intense craving for the drug itself.

Chronic abuse can lead to psychotic behavior, hallucinations, paranoia, violent rages, mood disturbances, suicidal thoughts, insomnia, psychosis, poor coping abilities, sexual dysfunction, dermatological conditions and "meth mouth", 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, intense craving for methamphetamine, anxiety, agitation, vivid or lucid dreams, suicidal temptation, psychosis resembling schizophrenia, paranoia and aggression (ONDCP 2003).

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[3] Although both methamphetamine and cocaine increase levels of dopamine, administration of methamphetamine in animal studies leads to much higher levels of dopamine, because nerve cells respond differently to the two drugs. Cocaine prolongs dopamine actions in the brain by blocking the re-absorption (re-uptake) of the neurotransmitter by signaling nerve cells. At low doses, methamphetamine also blocks the re-uptake of dopamine, but it also increases the release of dopamine, leading to much higher concentrations in the synapse (the gap between neurons), which can be toxic to nerve terminals (National Institute of drug abuse, 2014). More info at: http://www.drugabuse.gov

Production

The majority of methamphetamine distributed across the U.S. is made 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).[4]

Nevertheless, unlike heroin or powdered or crack cocaine, methamphetamine is a 100% synthetic product that can be easily and inexpensively manufactured with little equipment, few supplies, and almost no expertise in chemistry.

Ephedrine or pseudoephedrine is the most 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.[5]

For this purpose, cold tablets are mixed to sodium hydroxide, anhydrous ammonia, iodine, matches containing red phosphorus, Drano (a drain cleaner product), ether, brake and lighter fluid and hydrochloric acid. All these are legal products, which can be easily bought in local stores.

The entire chemical process, usually performed in self-made chemical labs hidden in flats, caravans, garages or hotel rooms, generally takes about two days' time and can result in hundreds of thousands of methamphetamine doses. "Mom and Pop" labs or small operations can produce methamphetamine easily and relatively cheaply. 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 a matter of hours (DEA, Congress, 2003).

Legislation

Because of ephedrine or pseudoephedrine are critical ingredients in methamphetamines' synthesis, the federal government has passed, in the last 25 years, several laws intended to cut the diversion of ephedrine and pseudoephedrine to illegal drug labs.[6]

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[4] Large domestic producers have used bulk supplies of tablets obtained from Canadian, Middle Eastern, Mexican or Far Eastern courses. As a result law enforcement sources report increased seizures of Asian pseudoephedrine tablets in California destined for super labs in that region (Hunt et. Al, 2006).

[5] Due to the clandestine nature of the process, information on the exact amount of cold medicines needed to produce one gram of methamphetamine is difficult to obtain. However, under perfect circumstances related to the quality of the inputs and the quality of the chemical process, 1 gram of pseudoephedrine translates in 0.9 gram of pure methamphetamines. As an example, 1 box of Sudafed – a decongestant and is used to treat nasal and sinus congestion –contains 12 pills of 30mg of pseudoephedrine. So, three boxes can be used to produce 1 gram of pure crystal methamphetamines. More info at: http://www.textfiles.com/uploads/methmethod.txt

[6] The first of these was the Chemical Diversion and Trafficking Act of 1988 (CDTA), which regulated ephedrine and pseudoephedrine in bulk powder form, but left processed forms unregulated. This was followed by the Domestic Chemical Diversion Control Act of 1993, which placed restrictions on OTC ephedrine products (e.g. tablets) and increased DEA oversight of suppliers. Then, the Methamphetamine Control Act of 1996 tightened regulations on the sale of products

This paper examines the effects of over the counter restrictions, implemented mainly in the year 2005, as a reaction to a rapid increase in the number of toxic labs where the manufacturing of this substance occurred.

These policies focused on controlling access to the methamphetamine precursor chemicals, ephedrine and pseudoephedrine, through: 1) quantity restrictions, 2) sales environment restrictions, 3) proof of identification upon purchase 4) logbook to prevent people from subverting the law by making repeated purchases.[7]

Policy activity restricting the access to methamphetamine precursor chemicals has not been limited to the state level. Federal legislation took place in 2006 through the Combat Methamphetamine Epidemic Act (CMEA) with the last provisions of the laws becoming effective the 30th of September 2006, setting a nationwide baseline standard for how to legally sell these products.[8]

Although the CMEA is effective nationwide, the State laws, which vary widely in content, are concurrently in effect.[9] If the State law is less strict than the Federal CMEA on a certain issue, then compliance with the State provision is insufficient, and the Federal law, as a practical matter, is controlling. Conversely, if the State law is stricter on a certain issue than the Federal CMEA, then the State law, as a practical matter, is the controlling standard on that point.[10]

[FIGURE 1]

The timing of the enactment of these laws needs to be taken into consideration. The state of Utah was the first to enact an internal regulation in 2001, followed by Oklahoma in 2004. The remaining states can be divided in 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,

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containing methamphetamine precursors over 24 grams, but contained an exception for "blister packs". Shortly thereafter, the Methamphetamine Anti-Proliferation Act of 2000 lowered the thresholds from 25 to 9 grams, but blister packs remained exempt (Dobkin et al., 2013).

7 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.

8 The Combat Methamphetamine Epidemic Act of 2005 (CMEA) was signed into law on March 9, 2006, to regulate, among other things, 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.

9 The most notable provisions of the Federal law are also addressed by many of the State laws: where products containing these chemicals can be sold, how and where the products must be stored, what amount may be purchased or sold in a single transaction or in a month, and whether purchasers must show identification and sign a logbook.

10 In both cases, of course, retailers and others subject to the laws must show compliance with both. Some States are a hybrid of the two situations, with the State law more lenient in some respects and stricter in others (ONDCP, 2006).

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.

The date of first enactment will give rise to different DD designs aimed at detecting the impact of OTC restriction on criminal activity. These different strategies will be described and explored in section IV.

III. Data Sources

This section first describes the various data sources used in the analysis. Then, it shows and discusses relevant descriptive statistics, postponing the discussion of other relevant statistics when pertinent in the empirical analysis.

Data

I have assembled an original annual panel dataset, encompassing 2,200 US counties in 50 states from 2001 to 2010.[11]

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).[12] 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. The FBI definition of the eight types of crime, as well as the explanation of the hierarchy rule, can be found in the data appendix.[13]

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[11] This represents almost 70% of all the US counties. The final sample is obtained merging county-level information across all the datasets that I will describe in this section. Missing observations on all datasets and the presence of data-corruption and differences in counties' names determines the size of the final dataset.

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

[13] In the FBI's Uniform Crime Reporting (UCR) Program, property crime includes the offenses of 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.

The "Uniform Crime Reporting Program Data: Supplementary Homicide Reports", accessed through the NAJCD, provides incident-based information on criminal homicides reported to the police. These homicides consist of murders, non-negligent manslaughter and justifiable homicides. The data contain information describing the victim, the offender, their relationship, the weapon used and – when known by investigators – the different circumstances surrounding the homicides. The latter information is of particular interest in this context and it will be carefully described when relevant for the empirical analysis.[14]

The Federal Bureau of Investigation's Hate Crime Statistics (HCS) provides incident-level data on hate crimes, which is also accessed through the NAJCD.[15] The Hate Crime Statistics Act of 1990 brought these data into existence. That Act requires the Attorney General to collect annual data on "crimes that manifest evidence of prejudice based on race, religion, disability, sexual orientation, or ethnicity, including where appropriate the crimes of murder, non-negligent manslaughter; forcible rape; aggravated assault, simple assault, intimidation; arson; and destruction, damage or vandalism of property".

The National Clandestine Laboratory Register, provided by the US department of Justice, contains data – from 2004 onwards – on the dates and addresses of the locations where law enforcement agencies reported they found chemicals or other items that indicated the presence of either clandestine drug laboratories or dumpsites.[16] I use this information to create a county annual measure of the number of meth labs seized by the local enforcement agencies, serving the analysis as a measure of the underlying clandestine local production of crystal methamphetamines.

Data on prices and purities of crystal methamphetamines, powdered cocaine, crack-cocaine and heroin are obtained from a public report "The Price and Purity

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14 This data are reported at the agency-level. I use crosswalks FBI data – accessed through NAJCD – to match police agencies to US counties. In less than 2% of cases, agencies' territory is included in multiple counties. Due to the impossibility of assigning the homicide to the correct county, I drop these observations when collapsing agencies measures into county-level measure of different type of circumstances surrounding the homicides. The crosswalk file is designed to provide geographic and other identification information for each record included in either the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) Program files or in the Bureau of Justice Statistics' Census of State and Local Law Enforcement Agencies (CSLLEA). The main variables each record contains are the alpha state code, county name, place name, government agency name, police agency name, government identification number, Federal Information Processing Standards (FIPS) state, county, and place codes, and Originating Agency Identifier (ORI) code. These variables allow a researcher to take agency-level data, combine it with Bureau of the Census and BJS data, and perform place-level and government-level analyses.

15 In this database, each observations represents a single incident report, that is used to construct county-level measure of the number of the total number hate crimes, by type of bias motivating the offense.

16 These data are public available at the following website: 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 likely not 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)

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).[17]

The Treatment Episode Data Set (TEDS) 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 to substance abuse treatment, and includes those admissions that constitute a burden on public funds.

The empirical analysis finally uses a wide set of county time-varying socio-economic controls, obtained from the US Census Bureau[18] and from the Bureau of Labor Statistics-Current Population.

Summary Statistics

Summary statistics for meth-labs seizures, violent and property crimes and drugs-related arrests are shown in table I, with variables expressed per 100,000 inhabitants.

[Table I]

Larceny is most frequent property crime, with a mean of 1,712 and a standard deviation of 1,034, followed by burglary, motor-vehicle theft and arson. Aggravated assault is the most frequent violent crime, followed by robbery, rape and murder with a mean of 3.5 and a standard deviation of 5.17.

Table I shows summary statistics drugs-related arrests, displayed separately for sale and possession separately. These data are divided in 4 categories: 1) synthetic narcotics (manufactured narcotics that can cause true drug addiction), 2) others dangerous non-narcotics (barbiturates and Benzedrine), 3) marijuana and 4) cocaine, opium or derivatives. Crystal methamphetamine, despite being a synthetic drug, it is officially included by law enforcement agencies in the category of "other dangerous non narcotics". Marijuana ranks first in both arrests for possession and sale, followed by cocaine, other dangerous non-narcotics and synthetic narcotics.

[Table II]

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[17] 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

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

Table II reports the descriptive all socio-economic county time-varying observables included in the analysis, normalized per 100,000 people when necessary. These are: income per capita, percentage of people below the poverty line, percentage of unemployment, social security recipients and the average monthly payment per subsidy. I also add the number of commercial banks and saving institutions in the county, the amount of banking and saving deposits, the population density of the county, police officers with arrest power, civilian employees. For brevity considerations, I omit the discussion of the summary statistics for these controls.

IV. The Effects of OTC restrictions on criminal activity

This section investigates the effects of OTC restrictions on crime. To this end, I first introduce and discuss the validity of the main DD design employed in this paper. Then, I present the results and a wide set of robustness checks. Finally, I briefly explore two different DD approaches, which play a marginal role in this analysis as well as in the subsequent investigation of the underlying operating channels.

Natural Experiment 1

Discussion of the empirical design

The implementation of this DD design aims to estimate the differences in criminal activity between 1) *Early Adopters* states, enacting OTC restrictions in 2005 and 2) *CMEA only states* that did not implement any internal law. Given that CMEA federal act was implemented nationwide in the last part of 2006, I limit this analysis within the period 2001 – 2006 included.

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

Table III serves this scope, summarizing mean and differences of critical variables related to drugs and crime penetration in the two groups. Specifically, column (1) and (2) report the mean of each variable for CMEA only Early Adopters states. Column (3) shows the difference between (1) and (2), reporting 10%, 5% and 1% significance levels. Means are computed in the pre-intervention period – from 2001 to 2004 – with variables normalized per 100,000 inhabitants.

[Table III]

Table III reveals that CMEA only states had significantly less methamphetamines production in their territory, information summarized by a 5.7 difference in meth-labs seizures per 100,000 inhabitants. Similarly, these states have significantly fewer hospitalizations due to meth abuse (-46.8), less drug-related arrests for sale (-11.1) and possession (-23.8) of other-dangerous non-narcotics, the FBI category containing crystal methamphetamines, and for sale and possession of synthetic narcotics (respectively -8.2 and 14.5).

Conversely, CMEA only states are characterized by a higher level of arrests for possession of marijuana (+53) and for sale and possession of cocaine, heroin, and derivatives, (respectively +24.9 and + 33.7).

This suggests that CMEA only states, while suffering fewer problems due to the presence of the methamphetamines market within their territory, were more exposed to crime-related problems arising from other extremely dangerous illegal drugs such as crack-cocaine and heroin.

The evidence on the pre-existing differences in criminal activity is more ambiguous. In fact, CMEA only states are characterized by a lower level of larcenies and burglaries (-275.9 and -164.03) but by a higher level of robberies (+36.34). No significant differences are detected for murders and aggravated assaults, with counties belonging to control states experiencing fewer rapes (-1.76) but more episodes of arsons (+4.29).

The existence of significant differences in baseline characteristics between Early Adopters and CMEA only states does not undermine the identification in a DD estimator, if the assumption of conditional parallel trends is satisfied.

Figure IV the evolution of criminal activity – in both categories of states – from 2001 to 2006, the period under analysis in this first empirical exercise.

[Figure IV]

Raw data reveals a reassuring pattern of crime in the periods before states' intervention for larcenies, burglaries, murders and assaults. The only exception is the visible drop for murders in CMEA only states from 2001 to 2002, due to the 9-11 terrorism act in the state of New York. Moreover, the graphical analysis uncovers a clear reduction in burglaries and larcenies in 2005 and in 2006 and a slight post-regulation reduction in Early Adopters states for murders and aggravated assaults, alongside a slight increase of these crimes in CMEA only states. This seems to suggest that criminal activity might have been relocated across borders as a response of Early Adopters' states OTC restrictions. This hypothesis will be tested in the last section of the paper.

Empirical strategy and results

All these premises lead to the following DD estimating equation:

$$y_{i,s,t} = \alpha_i + \delta_t + X'_{i,s,t}\beta_0 + \sum_{j=2001}^{2006} (treated * year_j)\, \beta_{1,j} + \varepsilon_{i,s,t} \qquad (1)$$

Where the subscript *i* indicates the county, *s* the state and *t* the year. Outcomes of interest are all reported crimes, expressed in the form of $log(1 + x)$, where x is the measure of each crime 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 the county belongs to a *CMEA only* state, and $year$, an indicator variable for each year in the sample.[19] In this specification, the omitted category is the interaction between the indicator variables "treated" and year=2004, the year preceding the enactment of OTC restriction in early adopters states. Robust standard errors are clustered at the state level.

I also include: 1) county fixed effects α_i , absorbing time-invariant unobserved characteristics, both related to the changes in crime and the states' decision of enacting the law; 2) year fixed effects γ_t, capturing common shocks across the entire sample and 3) a vector of county time-varying socioeconomic controls $X'_{i,s,t}$. 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, population density.

Table IVA shows the results for burglary columns (1) to (3) and larceny columns (4) to (6). Columns (1) and (4) show the baseline specification including year FE and states FE, columns (2) and (5) include county FE. In columns (3) and (6) I include all county observables.

[Tables IVA]

For the case of burglary, columns (1) – (3), I detect 8% to 11% reduction in the year 2005 and 2006, respectively. Coefficients are stable across all specifications, with associated significance levels always below 10%. While the coefficients before intervention grow in magnitude (from –0.06 in 2001 to -0.02 in 2004), no significant differential pre-trend between treated and control group is detected.

[19] While explicitly testing for the presence of differential pre-trends before intervention, this specification also allows for a flexible non parametric estimation of the effect of OTC restrictions on crime, needed due to different dates of enactment across states and the underlying annual nature of the data used in the analysis.

For the case of larceny, columns (2) – (4), DD estimates reveal a similar reduction of 9.7% in the year 2005 and of 13.5% in the year 2006. Coefficients are always below the 5% significance level and are stable across all specifications. As for the case of burglary, coefficients pre intervention grow in magnitude, (from -0.08 in 2001 to -0.04 in 2004), with a significant coefficient detected only in 2002, hence three years before intervention.

[Tables IVB]

Table IVB shows the results for aggravated assault, columns (1) – (3), and murder, columns (2) – (4). As for table IV-A, columns (1) and (4) show the baseline specification including year FE and states FE, columns (2) and (5) include county FE, columns (3) and (6) include county observables.

Results for aggravated assault are reported in columns (1) to (3). I detect a decrease of 6% to 7% 2005 with an associated p-value of 13%. The coefficient in year 2006 is around -6% but it is imprecisely estimated. For the case of murder, columns (4) – (6), I detect a decrease of 16% in 2005 and 10% in 2006. The coefficient in 2005 has a significance level below 10% across all the specifications, while the coefficient in 2006 is imprecisely estimated.[20]

Robustness Checks

Table V shows the robustness checks for estimating equation (1). Column (1) reports the results for larceny, column (2) for burglary, column (3) for aggravated assault and column (4) for murder. From panel A to H I only report the coefficients of the interactions between the indicator variables "treated" * "year 2005" (first row) and "treated" * "year 2006" (second row). In order to allow an easier comparison, Panel A reports the results obtained using estimating equation (1) that includes state FE, year FE and all county-level controls.

[Tables V]

Panel B shows the results when I add to the baseline specification both the measures of police officers with arrest powers and civilian employees. This control, while deepening the extent of the analysis, is not included in the baseline specification because it might be considered as a potential outcome of policies enacted by states' in their attempt to eradicate the problems related to methamphetamines production. Both the magnitude of the coefficients and the significance levels are stable across crimes and are almost identical to the baseline, reported in Panel A.

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

Panel C and panel D reports the results including state specific-linear trends and state-specific quadratic trends, respectively. The inclusion of state-trends pushes down considerably the estimates for all the category of property and violent crimes. This result opens up to various interpretations. From an economic perspective, state-specific trends might be an unobserved confounder in the analysis, if the endogenous decision to adopt OTC restriction is positively correlated linear or quadratic crime trends. In other words, if factors associated with rising crime have increased the pressure for the reform, the inclusion of state-specific time trends, while absorbing this effect, would push down the baseline estimates not including state-specific trends. From an econometric perspective instead, the inclusion of state-specific trends plausibly generates collinearity with the interactions of interest, (that uses a state*year variation) potentially altering and amplifying the effects of the laws on criminal activity.

[Figures V-A & V-B]

In figures V-A and V-B I plot the coefficients of the estimating equation (1) with and without state-specific linear trends. Despite the difficulty of disentangling these separate effects, I find reassuring that the inclusion of state-specific trends – while not driving the results that do exists without state-specific trends – strengthens the crime-reducing effects of OTC restrictions rather than weakening it.

Panel E 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.[21] Results are stable to this specification.

Panel F shows the results when I exclude counties belonging to California, Arizona and Texas, three early adopters states sharing the borders with Mexico, the larger supplier of methamphetamines in the United Stated via Mexican cartels.[22] Results are similar to the baseline for the case of larceny and murder. For burglary I detect an increase in the standard error raising to 12% the p-value associated to the effect in the year 2006. For aggravated assault the significance level in 2005 is now below 10%.

In Panel G I show the results including in the analysis the state of Kentucky, an early adopter state for which crimes information are extremely imprecise, with more than 40% of cases where crime is not reported at all (FBI coverage indicator equals zero). Results are also robust to this specification.

[21] The Coverage Indicator ranges from 100, indicating that all ORIs 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.

[22] Mexico is the largest supplier to the U.S. illicit drug market, with Mexican drug traffickers earning approximately 25 billion USD each year in wholesale U.S. drug markets (U.N. World Drug Report, 2011). In particular, Mexican drug cartels accounts for as much as 70 per cent of the meth sold, suggesting that small clandestine labs do not fulfill the entire demand for this drug in the United States (DEA, 2010)

Natural-experiment 2

In this DD design I estimate the differences in criminal activity between 1) the set of *Early Adopters* states *that implemented a law stricter than the CMEA federal act* and 2) *CMEA only states*.[23]

Hence, this empirical designs aims to examine the effects of the federal act in CMEA only states, eliminating the noise brought in the estimation by the set of Early Adopters states *enacting a regulation softer than CMEA.* The states excluded in this empirical exercise – in fact – were practically subject to an upgrade of the intensity of the internal regulation. After the 30th of September 2006, CMEA (rather than softer states' laws) was controlling the distribution of ephedrine or pseudoephedrine.

The estimation strategy used is identical in the spirit of equation (1) and it is defined by the following estimating equation:

$$y_{i,s,t} = \alpha_i + \delta_t + X'_{i,s,t}\beta_0 + \sum_{j=2001}^{2010} (CMEA * year_j)\,\beta_{1,j} + \varepsilon_{i,s,t} \qquad (2)$$

I hence define the indicator variable CMEA = 1 for CMEA only states and CMEA=0 for the pool of early adopters states that in 2005 enacted a legislation stricter then CMEA.

Figure V shows the plot of the coefficients with the 90% confidence interval for larceny, burglary, aggravated assault and murder. Similarly to estimating equation (1) the omitted category is the interaction between the indicator variables "CMEA" and "year 2004", outcome variables are expressed as the log normalized measure of crime per 100,000 inhabitants and standard errors are clustered at the state level.

[Figure V]

For the case of larceny, (top-left corner in figure VI), coefficients are significantly positive in 2005 and 2006, years in which early adopters states enacted OTC regulations. This reflects the already discussed decline in crime in all Early Adopters states due to OTC regulations implemented in 2005. A small and insignificant drop is observed in the year 2007, while the coefficients are again positive and significant in 2009 and 2010. The analysis suggests the presence of some persistence in the effects of OTC regulations on larceny in Early

[23] The states that enacted a stricter law then CMEA in 2005 are Arkansas, Delaware, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Tennessee, Texas, Virginia, Washington, Wisconsin,

Adopters states, but no significant effects in CMEA only states. Coefficients associated with all the other crimes are not precisely estimated.[24, 25]

V. Exploring the Mechanisms

This section explores potential mechanisms behind the reduction in criminal activity detected using estimating equation (1).

First, I estimate the effectiveness of OTC restrictions in targeting the domestic production of methamphetamines, including in the analysis DEA data on meth-labs seized by law enforcement agencies. Second, I examine the impact of regulations on meth trafficking and on the violent crimes associated with it. Third, I investigate the responses of the demand-side of the market, focusing on prices, arrests for possession and hospitalization from meth-abuse. Forth, I use FBI and ethnographic evidence to analyze the interaction between policies and peculiarity of this clandestine market, which might have been partly responsible for the reduction in crime. Finally, I use a combination of DD and IV designs, to quantify the overall causal effect that the domestic production of methamphetamines has on the proliferation of criminal activity.

Estimating the Disruption in the Domestic Production

States and Federal regulation were targeted to disrupt the domestic production of crystal methamphetamines, performed in clandestine labs. In the attempt to evaluate the results of these supply-side interventions, I introduce DEA data on the number of clandestine labs seized by law enforcement agencies. These data will serve the analysis as a measure of the underlying domestic production of methamphetamines occurring within county. Figure II shows a map of the

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24 Results are not reported for brevity considerations only and are available upon request. The absence of a significant effect might be reconciled with several explanations. From an econometric perspective, estimating equation (2) is low-powered, due to the necessary restriction of the analysis on only 22 US states. From an economic standpoint instead, the absence of effects might be related to three main reasons. First, criminals' ability to predict and to circumvent OTC restriction might have grown overtime, hence decreasing the crime-reducing effects of the laws. Second, CMEA only states were characterized by low levels of domestic meth production – as shown in table III – and suffered instead of much higher penetration of other drugs such as crack-cocaine and heroin. Hence, the legislation regulating methamphetamines might have had a lower impact on crime. Third, CMEA only states might have paid less attention to an effective implementation of these laws in states

25 In a third empirical strategy, I include ALL US states in the analysis, using the staggered implementation of the laws to identify the effects on crime. Nevertheless, the effectiveness of this analysis is prevented by several factors that are context-specific. First of all, the date of the enactment of the laws is very often the same across states, both in terms of years and specific dates. In fact, excluding Oklahoma and Utah, all the other states have implemented a law either in 2005 or in 2006. Hence, the high collinearity between the rollout dummy, year FE and the general decreasing trends in criminal activity prevents a clean identification of the effects of the laws on crime. Moreover, as discussed in the second DD design, more then 10 US states re-updated the internal law with the Enactment of the CMEA, hence generating further imprecision and noise in the empirical analysis.

distribution of labs in the United States in the year 2004, with categories expressed in percentiles only for illustrative purposes.

[Figure II]

The production of methamphetamines is spread across the entire territory of the United States, with a higher concentration in central-east states, particularly in Missouri, Tennessee, Arkansas, Kansas and Indiana.

[Figure III]

Figure III shows the total number of labs by year, with a decline of almost 50% from 2004 to 2005. The average number of methamphetamines labs is 2.17 per 100.000 inhabitants with a standard deviation of 6.38.

In this context, the ideal data would be obtained from a census of all the meth-labs, before and after the enactment of states' regulations, in treated and control states. These data clearly do not exist.

As discussed by Dobkin et al. (2014), the number of labs discovered by law enforcement agents is an unknown fraction of the total number of labs in operation. The probability of detecting a lab can be expressed as a function of law enforcement agents' effort, the likelihood of a lab catching fire due to the highly unstable synthesis process, the reports from the public to local enforcement agencies and other factors.

In my DD estimator, the relationship between the differential percentage change in the number of labs detected by law enforcement agencies and percentage change in the number of labs effectively in operation is given by the following relationship:

$$\%\Delta(D_T - D_C) = \%\Delta(p_T - p_C)[1 + \%\Delta(L_T - L_C)] + \%\Delta(L_T - L_C) \quad (3)$$

Where $\%\Delta = \frac{post-pre}{pre}$ where post and pre refers to the period before and after the regulation, the subscripts T and C indicate respectively treated and control states, D is the number of labs, p is the probability of detection and L is the number of labs effectively in operation.

If the probability of labs detection is unaffected by OTC regulations both in treated and control states, the differential percentage change in the number of discovered labs represents an unbiased estimate of the differential percentage change in the number of labs effectively in operation.

Nevertheless, anecdotal evidence suggests that OTC laws may have slightly increased the probability that a given lab will be detected in treated states post-regulations, as some police departments might have visited the residences of people whose names appeared repeatedly in OTC sales logbooks.

In this case, if the probability increases with the law in treated states ($\%\Delta p_t > \%\Delta p_c$), then using the percent change in the number of labs detected to estimate the per cent change in the number of labs in operation produces a lower bound estimate in the "true" reduction in the number of meth labs effectively operating.

Table VI shows the result of estimating equation (1). The number of clandestine labs seized by law-enforcement agencies is available from 2004 onwards. I hence delimit the analysis from year 2004 to year 2006 included. All the other details of this regression analysis are the same reported when describing estimating equation (1).

[Table VI]

Column (1) shows the results for the baseline specification, when I include year FE and state FE. In column (2) I add to the baseline specification county FE. In column (3) I include all county observables. In column (4) I add as potential confounding controls police officers with arrest powers and civilians. The sign of the coefficient is negative as expected, across all specifications. As shown in column (1), the introduction of the law reduces the number of meth-labs by 41%. The inclusion of county FE and all controls moves the estimates to -37%. Coefficients are precisely estimated with an associated significance level always below 1%.[26]

Exploring the Operating Channels

Distribution and violence

The exit from the market of a multitude of meth-producers controlling low and medium capacity labs – established in the preceding subsection – might have reduced the level of competition in the streets among drug dealers, hence lowering the systemic violence associated with the sale of methamphetamines. This dynamic might in part explain the drop in murders and aggravated assaults, detected in the first part of the paper.

In this section of the paper I test this hypothesis analyzing the impact of OTC restrictions on 1) arrests for sale of "Other Dangerous non Narcotics", the FBI category including crystal methamphetamines and 2) the number of homicides

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[26] These estimates are almost identical to the results of Dobkin et al. (2014). In particular, they show that the reduction was large for labs with capacity less than two ounces and for labs with capacity between two and eight ounces at approximately 32 and 54%. For the largest labs the reduction was smaller at 22% and not significant at the .05 level. They compute a decline of 25% in the overall domestic production of methamphetamines.

that occurred in circumstances related to gangs violence and illegal drug trafficking. For both specifications I use estimating equation (1). Table VII, column (1) reports the results with outcome variable being arrests for sale of other dangerous non-narcotics.

[Table VII]

This specification includes county FE, year FE and all county observables. While the effect is negative but highly insignificant in the year 2005, I detect a 23% reduction in the 2006. This coefficient is significant at the 10% level. In column (2) I add state-specific linear trends. The result is robust to this specification, with a coefficient of -30% in 2006, with an associated significance level below 5%.

Despite the sharp reduction in the arrests for other dangerous non-narcotics, plausibly due to the drop in the domestic production of crystal methamphetamines, no significant change is detected with the violence associated with drug trafficking expressed by homicides due to narcotic drug offense, gangland killings and juvenile gangs killings.

Prices and the Demand-Side of the Market

OTC restrictions, disrupting the local production of methamphetamines, might have reduced the availability of the illegal substance, increasing its price and – hence – lowering consumption. This dynamic might hence explain the reduction in criminal activity connected with drugs' abuse. This section explores this hypothesis analyzing data on prices and purities, arrests for possession and meth-related hospitalizations.

Data on prices and purity are expressed per pure gram of methamphetamine for three different weight categories, summarizing three different levels in the illegal-drug distribution chain (0.1 – 10g, 10 – 100g and >100g). Quarterly prices in 2007 US dollars are aggregated at the national level, hence preventing the analysis using a DD design. Nevertheless, Figure VII-A reveals an interesting pattern on the evolution of both prices and purity of crystal methamphetamines.

[FIGURES VII]

The first vertical line represents the 3rd quarter 2005, period in which 70% of early adopters stated enacted OTC restrictions, while the second vertical line represents the quarter where CMEA was introduced. Considering the top pick in price relative to the second quarter of 2005, the price for 1 gram of methamphetamines in quantities below 10 grams raised by 108%, the price for quantities between 10 – 100 grams raised by 70%, while the price for quantities more than 100 grams rose by 55%. The graphical analysis also suggests a response in the production, showing a more homogeneous drop of around 35-40% in the purity of the substance in the same time frame.

Both the effects on prices and purity, while showing a further response from this clandestine market plausibly due to the disruption in low and medium domestic labs, are short lived, suggesting that methamphetamines from Mexican cartels fill the void in the clandestine market.[27]

To get a better sense of the changes in the demand-side of the market, I analyze data on arrests for the possession of other dangerous non-narcotics, the FBI category including crystal methamphetamines. Table VIII reports the results. I do not detect any significant pattern due to OTC restrictions. In particular, for the case of arrests due to possession, I detect a positive coefficient in 2005 and a negative coefficient in 2006 both imprecisely estimated and of difficult interpretation.

I also detect an important increase of 28% in the number of hospitalization due to meth abuse in the years 2005, nevertheless imprecisely estimated. This seems to suggest that a potential operating channel in the reduction of crime might be connected with the incapacitation of segment of abusers with possibly high propensity to generate crime. Nevertheless, the lack of precision in the estimates and of any sort evidence supporting this argument imposes caution in the specific interpretation of these findings.

Retail Market Characteristics & Ethnographic Evidence

The decline in criminal activity might be further reconciled with some of the unique features of the retail market connected to domestic production of meth. This subsection outlines these peculiarities, formulating some hypothesis partly validated by ethnographic evidence describing the behavior of meth producers and consumers before and after the enactment of OTC restrictions.

Typically, imported illegal drugs such as cocaine or heroin have a hierarchical and complex distribution system. These substances originates from agricultural products that need to be harvested, processed at several junctures, shipped, and eventually packaged for different levels of distribution. These steps involve several people at different levels of the distributional chain: growers, extractors or producers, transporters, smugglers, distributors and numerous other people that are needed to move product across borders before it gets to the final customer.

Methamphetamine, by contrast, is a drug synthesized using widely available chemical precursors, with receipts that can be easily found online and with an

[27] Moreover, the regression analysis in Dobkin et al. (2014) does not reveal significant effects on prices and purity as a consequence of OTC restrictions, suggesting that the increase in prices – that might have reduced the consumption of methamphetamines – might be only part of the reasons explaining the reduction in criminal activity.

easy production process that can be performed without any particular knowledge of chemistry.

For this reason, the meth "cook" – particularly in the case of smaller operations mostly targeted by OTC restrictions – is often a heavy meth user that turned into a producer. The "cook" decides to face the risk of a heavier criminal conviction to sustain the drug habit generated by the high power of addiction of the substance. Moreover, the ease of production translates into a lack of specialization across different roles in the distributional chains, which generates segmentation in the retail market. In fact, meth produced in small and medium "Mom and Pop Labs" is typically sold to a close network of family and acquaintances – usually sharing a high level of addiction with all the relative consequences – rather than to strangers in the streets.[28]

This framework opens up to the possibility that the decline in crime might be partially due to the reduction of consumption in networks of drug abusers that were hit by the impossibility to directly produce the synthetic substance. This dynamic, together with the sudden increase in prices and with the difficulty to find the substance at favorable prices outside the close network of acquaintances, might have curbed the immoderate consumption within networks of extreme abusers that – plausibly – where characterized by a high propensity to generate both property crimes (to sustain the habit or to finance the production) and violent crimes (mainly deriving from the psychosis due to intense abuse).

Ethnographic evidence sheds some light on this and on alternative hypothesis. In a study by Lopez (2014) of 38 meth-users women convicted in Missouri, nearly half of the women suggested that it became more difficult to purchase and manufacture meth as a result of OTC restrictions. As a result, it became more difficult to cook large quantities of meth at one time after the laws changed: "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. The women in the sample, despite heavy drug use and involvement in other crimes, were in many cases "restrictively deterred". Though they all

[28] 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 larger or more organized networks, a large number of small groups, weak or little organizational structure and fluid group membership characterize this type of network where meth is produced, consumed and sold within a restrict number of people. 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 and typically happen indoor rather than outdoor. In Sacramento, 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 sites with established meth use (San Diego, Phoenix, Portland) have similar data.

eventually were caught, the women made strategic moves—reducing or changing their involvement—to try and reduce their likelihood of arrest and severe punishment. Some of them also made the decision to quit using prior to arrest, though typically for other reasons.

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, while many of these respondents had decreased their use and production of methamphetamine at the follow-up, they attributed these decreases to other factors (e.g., personal, health and family problems related to meth use) and not directly to the new laws (Sexton et al., 2008).

Quantifying the Effects of Domestic Production on Crime: an IV design

In this part of the paper I quantify the overall effects of domestic production on crime. To achieve this purpose, I combine the DD strategy outlined in estimating equation (1) with an IV approach. The idea is to use as an instrument for the number of meth-labs seized by law-enforcement agencies, the variation generated by the enactment of the states' laws in the year 2005.

Equation (5) shows the first stage regression while equation (4) reports the IV estimating equation:

Two stage least squares:

$$y_{i,s,t} = \alpha_s + \delta_t + X'_{i,s,t}\beta_0 + \widehat{meth\_labs}_{i,s,t}\beta_1 + \varepsilon_{i,s,t} \qquad (4)$$

First stage:

$$meth\_labs_{i,s,t} = \gamma_s + \eta_t + X'_{i,s,t}\beta_2 + (treat * post)\beta_3 + \zeta_{i,s,t} \qquad (5)$$

Due to data limitation on meth-labs I restrict the analysis from 2004 to 2006. I use as instrument the interaction between the treated dummy and the dummy post (taking the value 0 in 2004 and 1 in 2005 and 2006). As in the earlier analysis, reported crimes and meth labs are expressed as $ln(1 + x)$, where x is the relevant variable expressed per 100,000 inhabitants. The baseline specification, due to the presence of only three years of data includes state FE rather than county FE. County FE will be added in the subsequent robustness check.

Results of the first stage regression are reported in table VI column (1). The sign of the instrument is negative as expected (-41%), significant at the 1% level. The F-statistic on the excluded instrument has a value of 104.5.

Tables IX-A and IX-B show the results of the OLS and IV specification. Table IX-A reports the results on theft crimes (larceny, burglary and motor-vehicle thefts). Table IX-B shows the results for violent crimes (murder, aggravated assaults and rapes).

[Table IX-A / IX-B]

For the case of property crimes, the elasticity on larceny and burglary is positive 0.25 and 0.3 significant, in both cases, at the 1% level. The elasticity in case of motor-vehicle thefts is 0.11 with a p-value of 13%. For violent crimes I detect an elasticity of 0.34 for rape, 0.2 for assault and 0.35 for murders. All these coefficients are precisely estimated at the 1% or 5% level. Table X shows the IV results with county FE. Estimates are unchanged in terms of magnitude and precision.

IV estimates are three to five times larger than OLS for both violent and property crimes, with the only exception being murder where IV estimates are 30 times larger than OLS. Three reasons might explain the negative bias in the OLS coefficients.

First of all, idiosyncratic and systematic measurement error – associated with the use of meth-labs seizures as a proxy for the underlying covert production of methamphetamines – generates attenuation bias in the OLS estimates. Chalfin and McCrary (2014) present evidence on the degree of measurement error in the basic dataset on police used in the U.S. literature, the Uniform Crime Reports (UCR). Consistently with the majority of my results they show that prior regression-based estimates are too small by a factor of four or five. This might be considered as a lower bound for this analysis, if we assume that the extent of measurement error is higher in the attempt to measure an intrinsically covert activity as meth production using data on seizures, rather than FBI data for police employment.

A second possibility can be associated with the fact that the positive selection of domestic meth production in areas with increasing crime trends might be partially counterbalanced by the attempt to hide the illegal activities in areas with lower probability of detection by law enforcement agencies.

Finally, IV might be larger than OLS, because IV is estimating the local average treatment effect (LATE) rather than the (ATE). In particular this reconciles with the evidence suggesting that states laws were targeting segments with an higher propensity to commit crimes, in this case the segment of the market associated with small and medium meth-producers.

VI. Other Results

In this last section of the paper I show three different sets of results. First, I further explore the drugs-violence link, exploiting FBI information of exact circumstances under which homicides occurred and on hate crimes, episodes of "apparently irrational" violence motivated by any sort of religious, racial or sexual bias. Then, I examine possible unintended consequences of OTC restrictions explicitly focusing on 1) substitution toward the demand or supply of other illegal substances and 2) crime's spillovers in counties sharing the borders with treated states.

Investigating the Drugs Violence Link

Table XI shows all the FBI categories of circumstances that lead to murders, number of episodes for the period spanning 2001 to 2006 and relative frequency.

[TABLE XI]

To perform the empirical analysis I have grouped the violent instances in 5 broader crime categories: 1) theft, 2) sex, 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 (1) with same empirical details applying.

Results are shown in table XII with one column reporting the results for each violent-crime category. I detect an 8.2% reduction of murders connected to brawls and violent altercations in the year 2005. This coefficient is significant at the 10% level. No significant effect is detected on the other murder categories.

[TABLE XII]

I then extend the analysis focusing on the effects of OTC regulations on hate crimes. These crimes are bias-motivated, which the Hate Crime Statistics Act of 1990 defines as "offenses against a person or property motivated by bias toward race, religion, ethnicity/national origin, disability, or sexual orientation".

Mcdavitt et. Al (2002) analyzes Boston police case files of the hate crime. 66% of the cases under review in this study were motivated by a desire for excitement or thrills. In this category of crimes, youths often told police they were just bored and looking for some fun. In 91% of these thrill-motivated cases, the perpetrators reported having left their own neighborhood to search for a victim in a gay bar, a temple in another part of town, or a minority neighborhood. Their target was not selected randomly but was chosen because the offender perceived that the victim was somehow different. Although the underlying factor was bigotry, according to interviews with CDU investigators, the attack in these thrill-motivated cases was triggered by an "immature desire to display power and to experience a rush at the expense of someone else". In discussions with the police, several of these young offenders revealed that their only benefit from the attack was some vague sense of their own importance: a sadistic high as well as bragging rights with their friends who believed that hatred was cool.

[Table XIII]

Table XIII shows the distribution of episodes in the United States from 2001 to 2006, by type of bias. Hate crimes' episodes are mainly divided in crimes against: black 35%, white 10%, Jewish 11%, Hispanic 7%, Male-Homosexuals 10%.

Hate Crimes are mainly violent crimes: destruction/vandalism represents 33% of episodes, intimidation 30%, simple assault 18% and aggravated assault 10%.

I use estimating equation (1). Results are shown in tables XII column (6) for the grouped category of hate crimes. I detect a 10% increase in hate crimes in the year 2005 even if the presence of negative pretend in the year 2003 imposes caution in these estimates.

Substitution toward other illicit substances

I now try to detect possible side effects that the OTC restriction might have generated shifting the both the demand or supply side of the market towards other illegal substances. To this end, I use data on arrests for sale and possession of other categories of illegal substances: marijuana, cocaine and synthetic narcotics. Results are shown in table XIV.

[Table XIV]

No significant effect is detected. The absence of any findings in the analysis of drugs-related arrests, alongside the graphical evidence reported in figure VII-A and VII-B on prices and purities of crack-cocaine, heroin and powder cocaine seems to suggest the absence of any sizable substitution effect across illegal substances.

Cross-Borders Spillovers

In the last section of the paper I investigate the presence of possible unintended consequences of the states' laws due to relocation effects in production and criminal activity that might have happened across states-borders. I use the following estimating equation:

$$y_{i,s,t} = \alpha_i + \delta_t + X'_{i,s,t}\beta_0 + \sum_{j=2001}^{2006} (bordering * year_j)\,\beta_{1,j} + \varepsilon_{i,s,t} \qquad (6)$$

Importantly, this last quasi-experimental design is limited only to counties belonging to CMEA only states. I assign an indicator variable bordering=1 to counties sharing the borders with states that adopted an OTC regulation in 2005, while I assign the value bordering = 0 to non-bordering counties. Results are shown in table XV.

[Table XV]

Each column reports the results of the same specification for each different outcome, respectively: meth-labs seizures, larceny, burglary, aggravated assault and murder. I do not detect any significant effect on meth-labs seizures nor in criminal activity.

VII. Conclusions

This paper offers one of the first systematic empirical investigations of the effect of the market of illicit drugs on criminal activity.

Motivated by the richness of anecdotal evidence, I look at this issue through the lens of crystal methamphetamine, a neurotoxic illicit substance widely diffuse in the United States. I use as a source of exogenous variation the implementation of OTC regulation that restricted the access to methamphetamine precursor chemicals.

A variety of diff-in-diff and IV approaches shows: 1) a reduction of property and violent crimes of 10% to 15%; 2) a 37% decrease in clandestine meth-labs seizures and 3) an underlying crime's elasticity of around 0.3; 4) 8% reduction in murders due to brawls and violent altercations but a more controversial increase in hate crimes 5) no spill-over effects on arrests for sale or possession of other drugs.

This paper suggests new directions for future research. A direct spin off of this work would be the analysis of shocks on the supply, distribution or consumption of other dangerous drugs such as crack-cocaine and heroin. Moreover, entering the "black box" of the mechanism linking proliferation of drugs and criminal activity is critical for the understanding of criminal behavior. Three main mechanisms seem in fact to play an important role in this context: economic, systemic and psychological. Disentangling these three channels might help to shape specific policy interventions that seek to reduce the impact that the proliferation of drugs can have on criminal behavior. This and other interesting aspects are left for future research.

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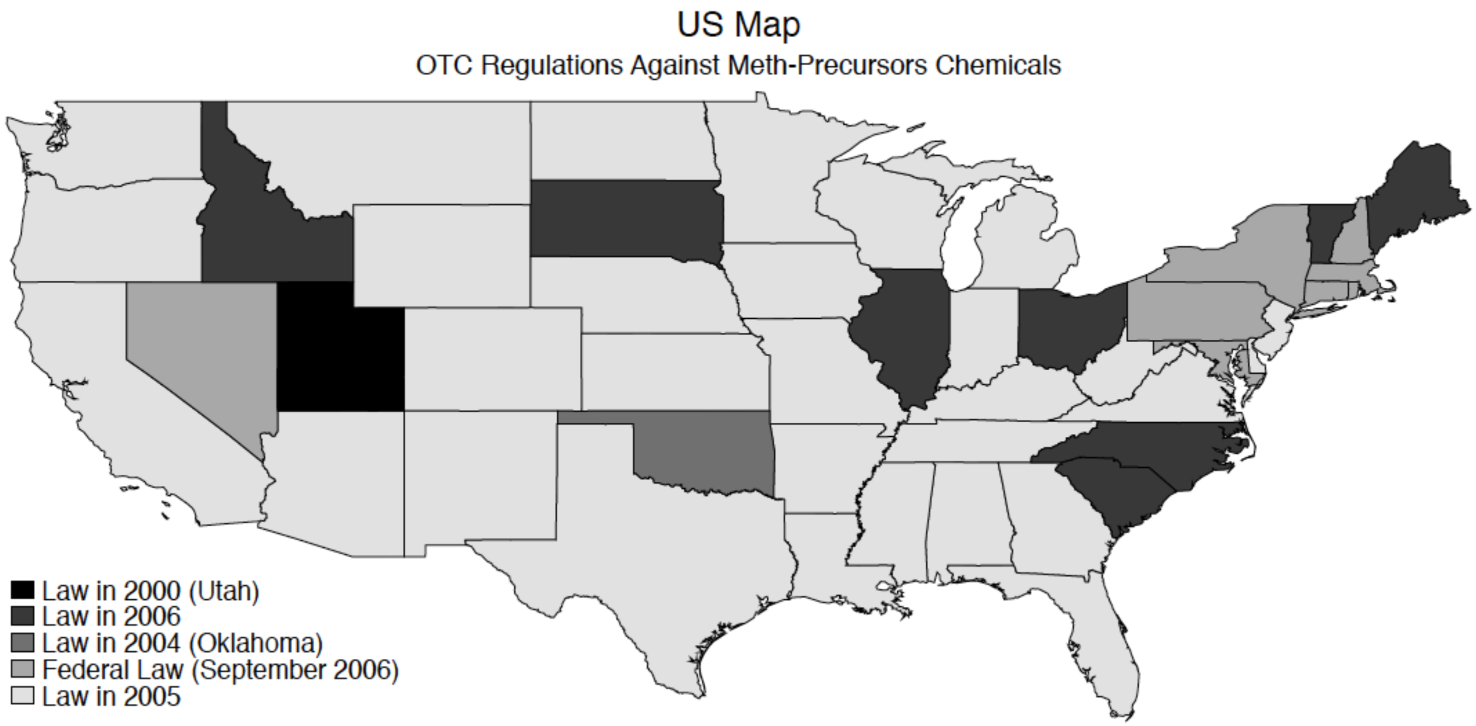
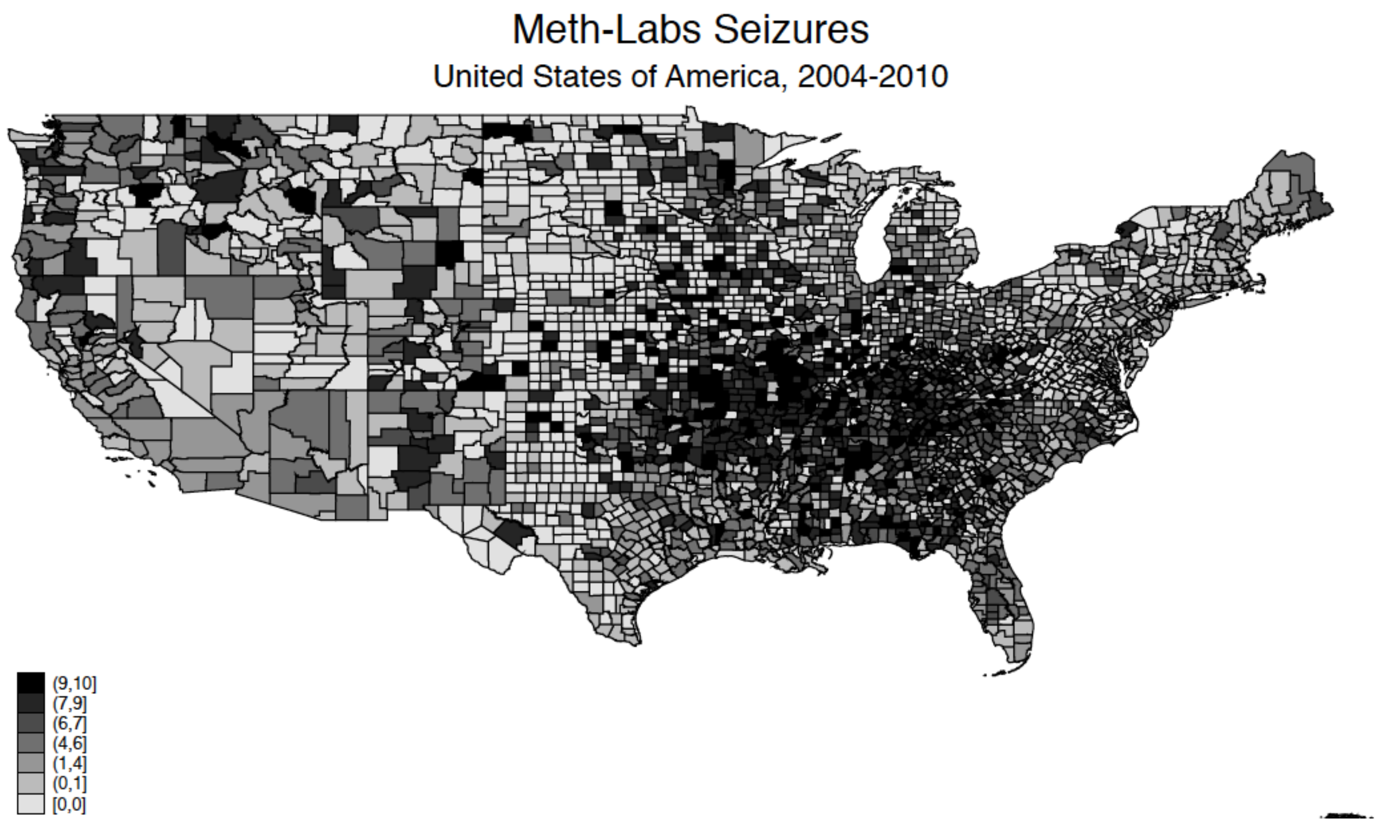
FIGURE I



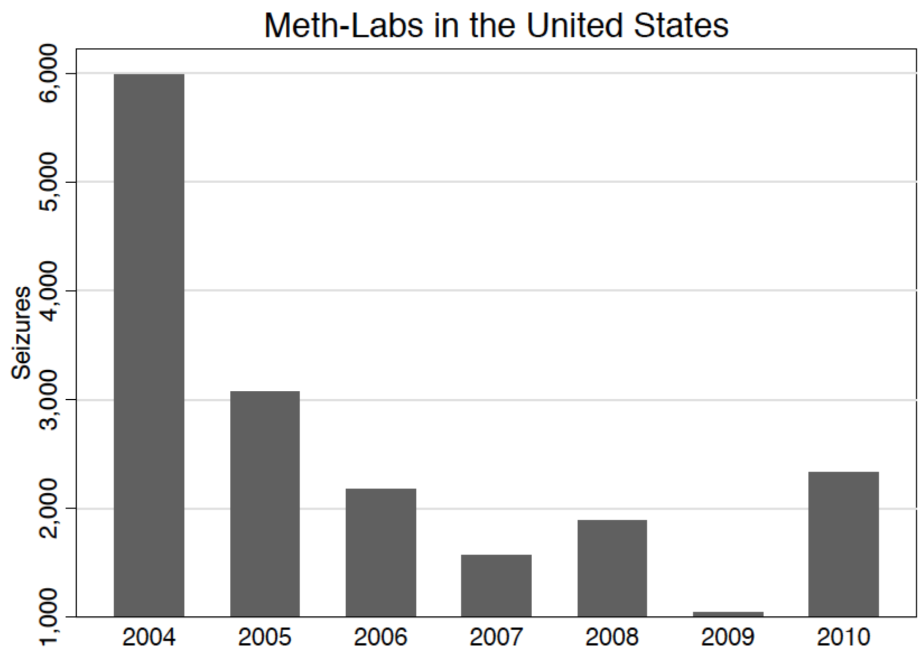
NOTES: This Figure shows a map of the United States that highlights the first year of enactment of OTC restrictions (both states and federal regulation). Alaska and Hawaii are eliminated from the figure for illustrative purposes only. Source (DEA, 2007). Utah was the first to enact an internal regulation in 2001, followed by Oklahoma in 2004. The remaining states can be divided in 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, 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.*

FIGURE II



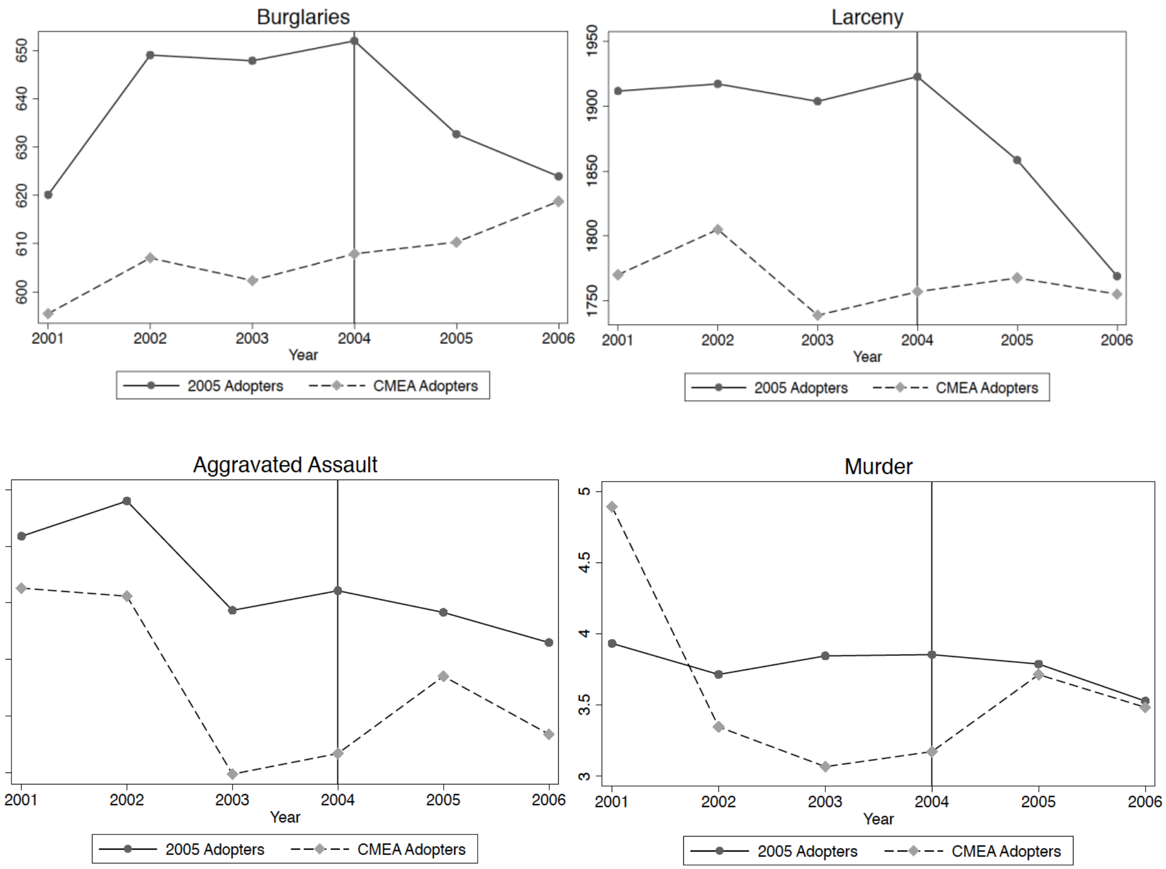
NOTES: This Figure shows a map of the United States showing the distribution in deciles of meth-labs seized by law enforcement agencies. Alaska and Hawaii are eliminated from the figure for illustrative purposes only. Source (DEA, 2012).

FIGURE III



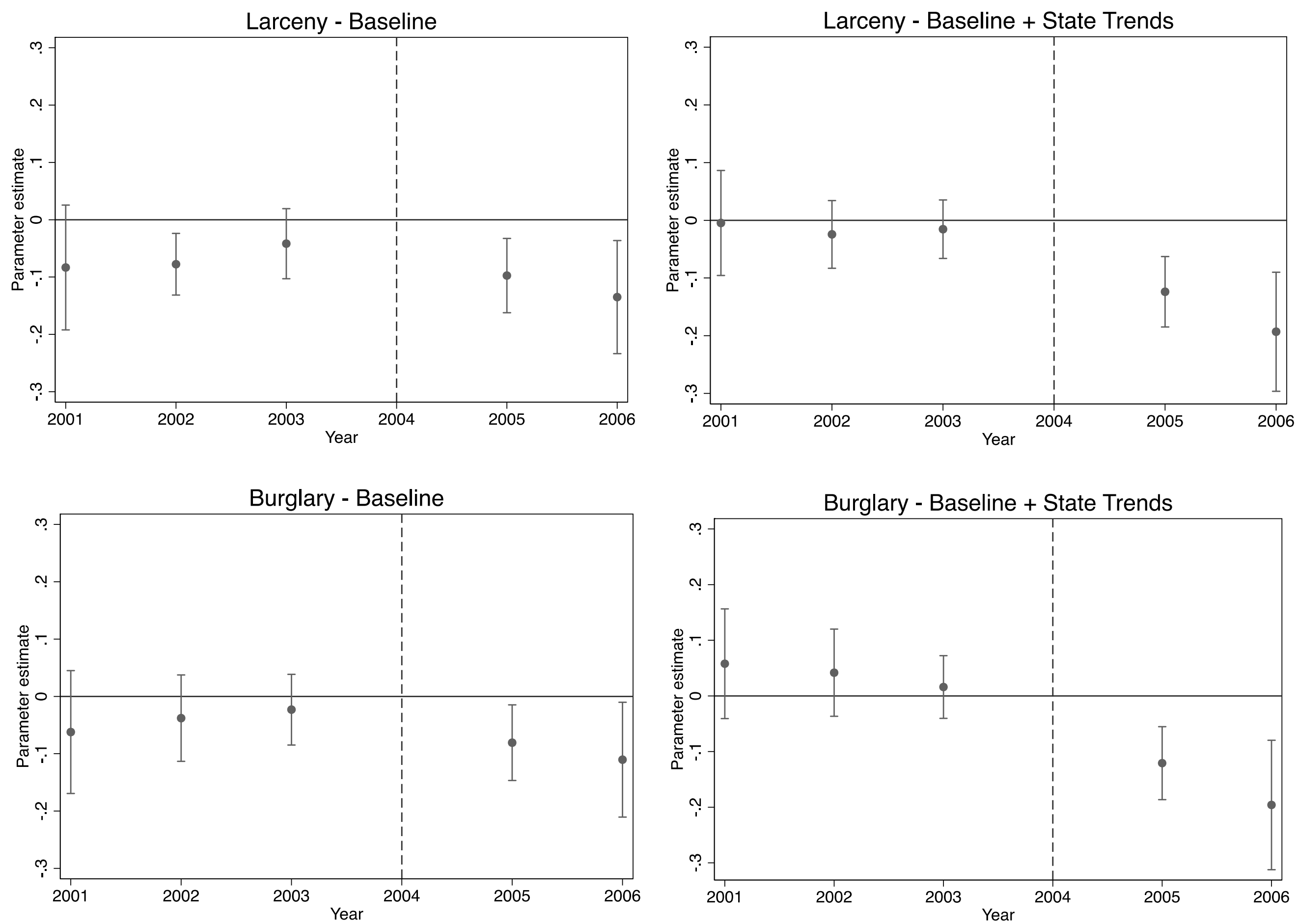
NOTES: This Figure shows the number of meth labs seized by law-enforcement agencies in the United States, from 2001 to 2010. Source (DEA, 2012).

FIGURE IV



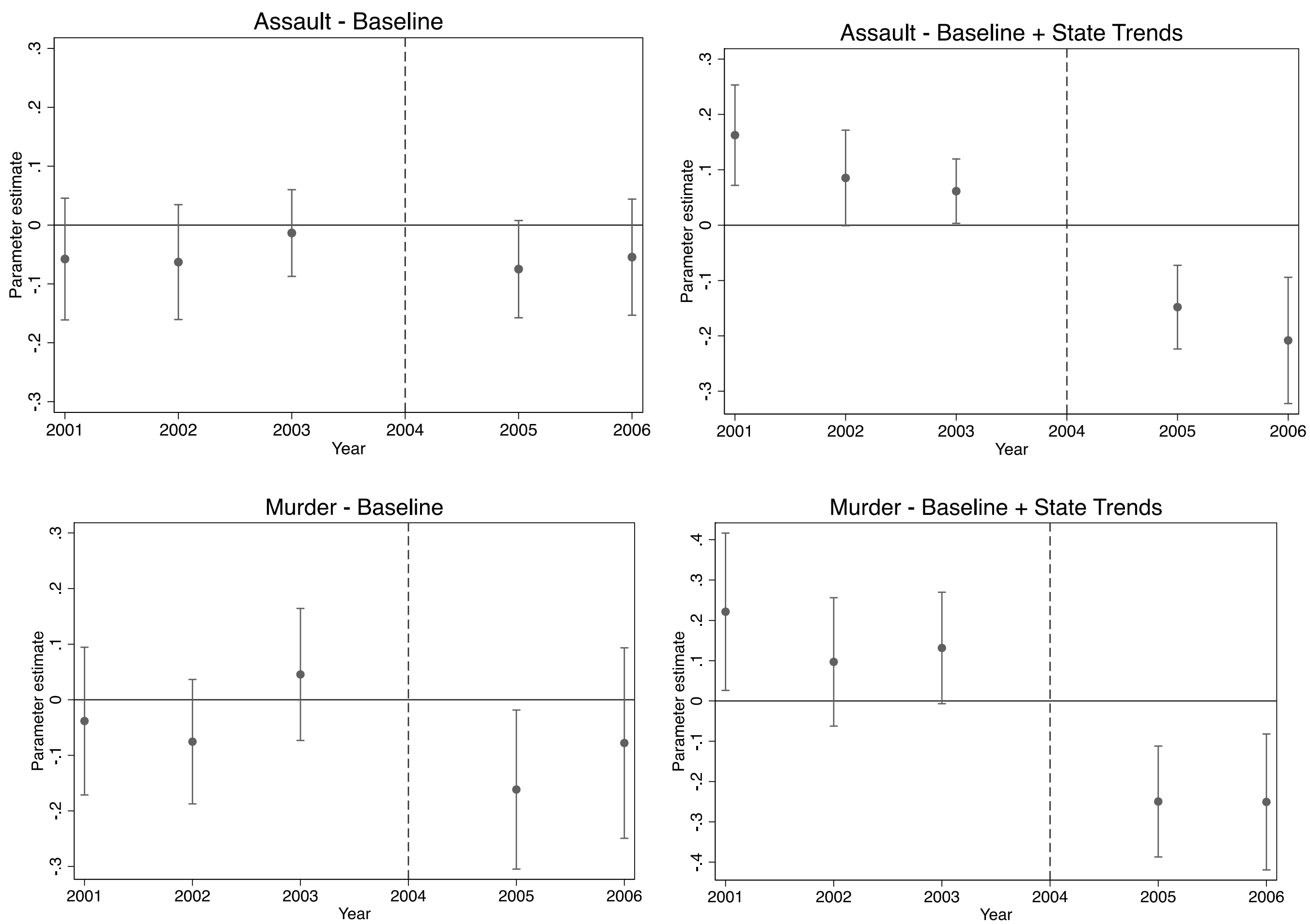
NOTES: This figure shows the evolution of burglarues, larcenies, aggravated assaults and murders in states that adopted an internal regulation in 2006 ("2005 adopters") and in states where only the federal act CMEA was passed the 30th of September 2006.

Figure V-A



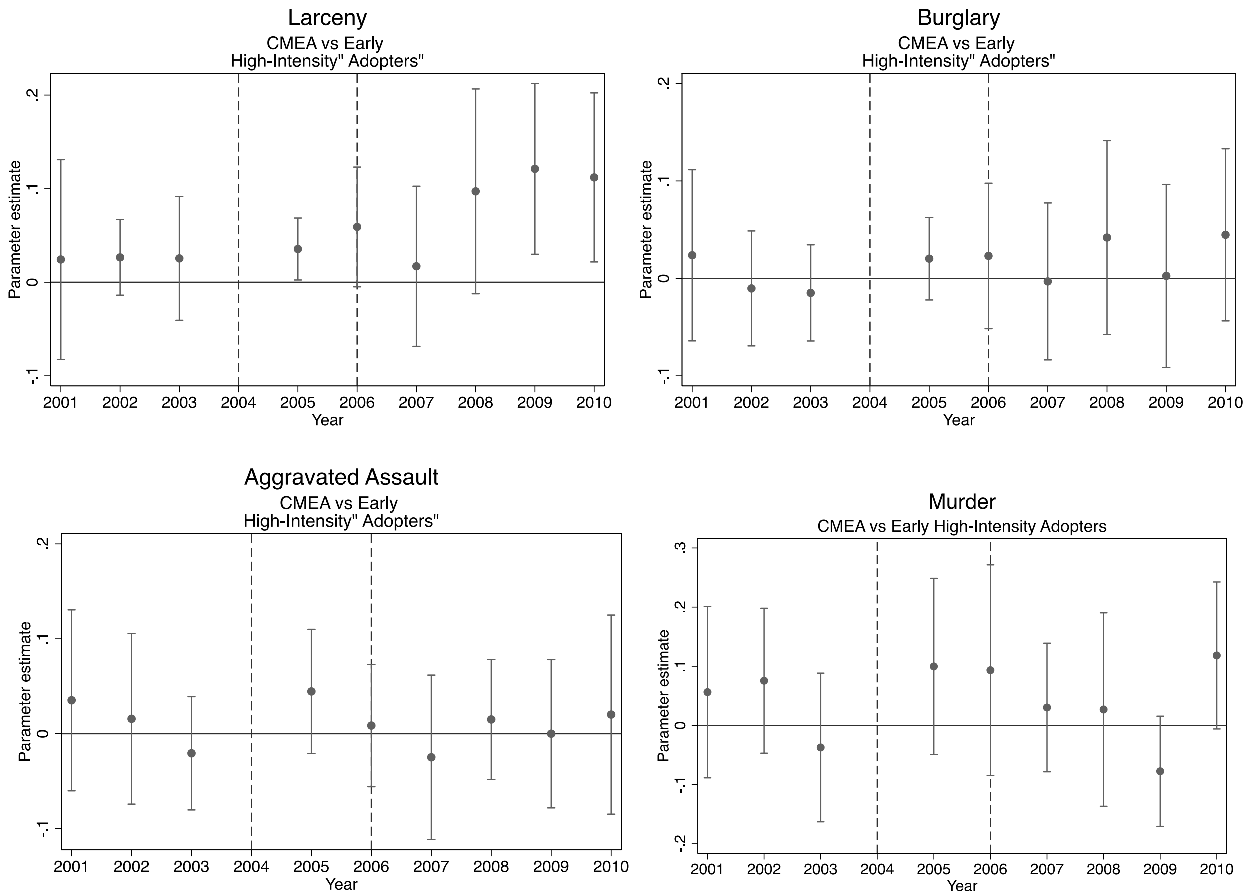
NOTES: This figure shows the plot of the coefficients obtained using equation (1) for burglaries and larcenies. The baseline includes county FE, year FE and all county observables.

Figure V-B



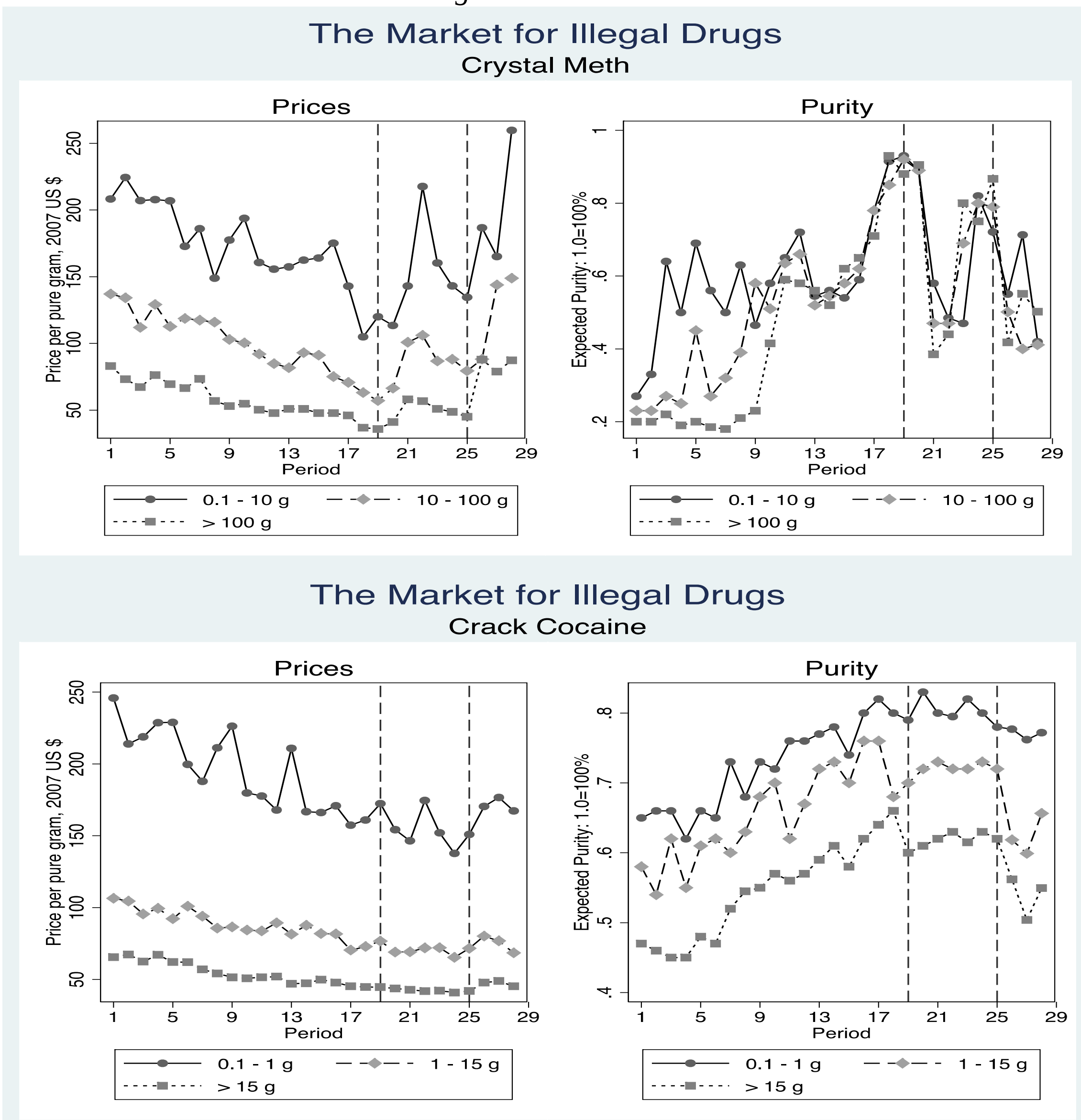
NOTES: This figure shows the plot of the coefficients obtained using equation (1) for aggravated assault and murder.

FIGURE VI



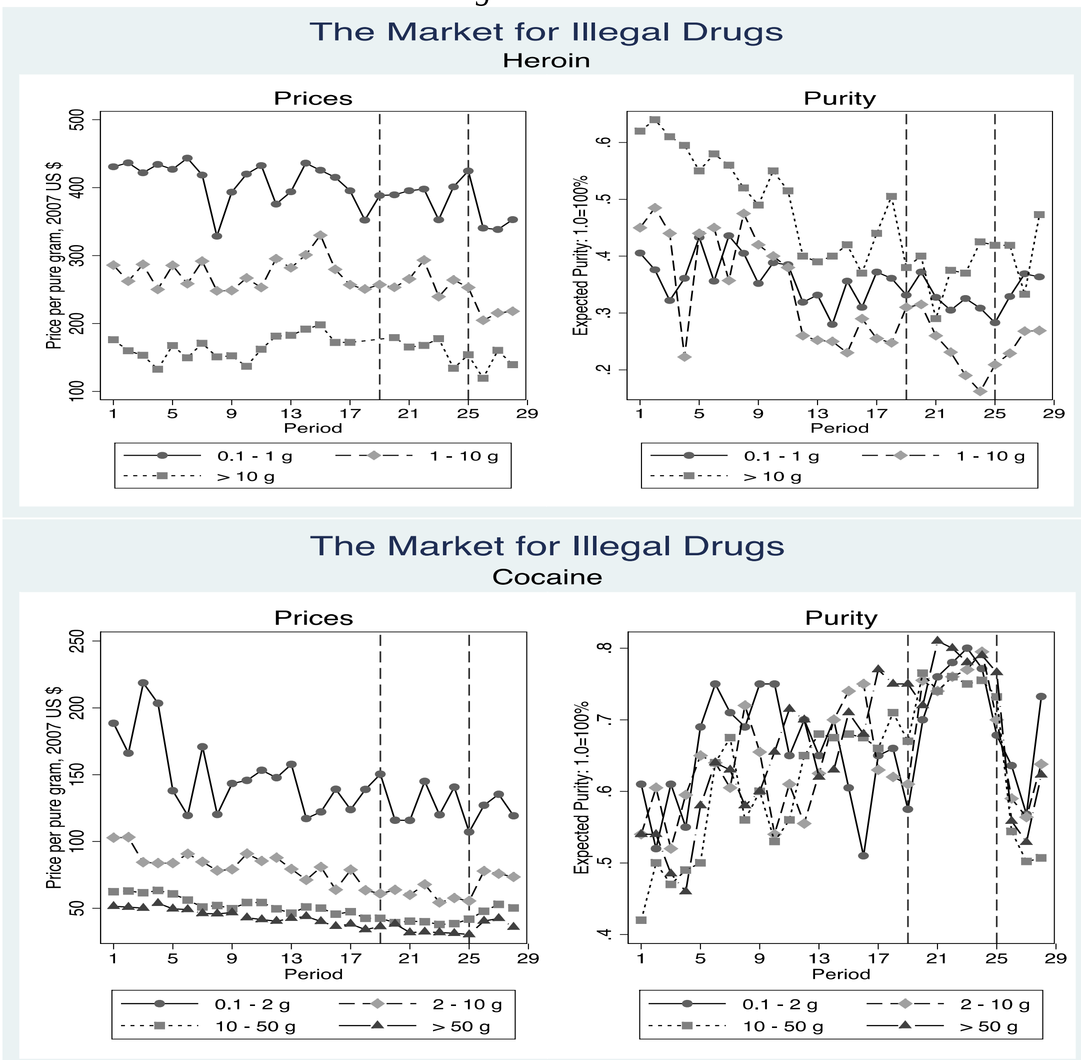
NOTES: This figure shows the plot of the coefficients with the 90% confidence interval using estimating equation (2) for larceny, burglary, aggravated assault and murder. I use the following estimating equation: $y_{i,s,t} = \alpha_i + \delta_t + X'_{i,s,t}\beta_0 + \sum_{j=2001}^{2010}(CMEA * year_j)\,\beta_{1,j} + \varepsilon_{i,s,t}$ *. I hence define the indicator variable CMEA = 1 for CMEA only states and CMEA=0 for the pool of early adopters states that in 2005 enacted a legislation stricter then CMEA. The omitted category is the interaction between the indicator variables "CMEA" and "year 2004", outcome variables are expressed as the log normalized measure of crime per 100,000 inhabitants and standard errors are clustered at the state level.*

Figure VII-A



Notes: This figure shows the evolution of prices and estimated purities for crystal methamphetamines and crack cocaine. Data are obtained from a 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 three different weight categories, summarizing three 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 3rd quarter 2005, period in which 70% of early adopters stated enacted OTC restrictions, while the second vertical line represents the quarter when CMEA was introduced.

Figure VII-B



Notes: This figure shows the evolution of prices and estimated purities for heroin and powdered cocaine. Data are obtained from a 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 three different weight categories, summarizing three different levels in the illegal-drug distribution chain (0.1 – 10g, 10 – 100g and >100g). 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 3rd quarter 2005, period in which 70% of early adopters stated enacted OTC restrictions, while the second vertical line represents the quarter when CMEA was introduced.

Table I - Crime-Related Descriptive Statistics

	(1) N	(2) Mean	(3) S.D.	(4) Min	(5) Max
Meth-labs seized	15,246	2.17	6.38	0	152.7
Larceny	21,776	1,712	1,034	0	6,922
Burglary	21,776	616	399.7	0	2,960
Robbery	21,776	49.53	70.73	0	763.9
Motor-Vehicle Theft	21,776	177	173.6	0	2,385
Murder	21,776	3.57	5.17	0	81.17
Aggravated Assault	21,776	221	194	0	2,336
Rape	21,776	26.38	22.53	0	513.5
Arson	21,776	16.84	19.21	0	373.9
Cocaine Sale	21,776	28.42	52.78	0	1,418
Marijuana Sale	21,776	29.94	37.85	0	787.5
Synthetic Sale	21,776	12.05	30.31	0	505.4
Other Sale	21,776	19.73	45.40	0	1,660
Cocaine Possession	21,776	59.24	88.45	0	2,176
Marijuana Possession	21,776	224.2	197.8	0	7,080
Synthetic Possession	21,776	28.01	50.06	0	1,072
Other Possession	21,776	54.29	83.85	0	2,263

Notes: Variables standardized per 100.000 people, by county. Source NACJD (2001 - 2010), DEA 2004-2010.

Table II - Descriptive Statistics

	(1) N	(2) Mean	(3) S.D.	(4) Min	(5) Max
Banks and Savings Institutions	21,775	40.68	18.08	0	257.5
Banks and Savings Deposits	21,775	14.65	14.20	0	560.3
% Unemployment	21,734	6.404	2.633	1.600	29.90
Income Per Capita	21,746	29,017	7,739	10,514	124,742
% Poverty	21,776	0.149	0.0628	0	0.505
% Social Security Recipients	21,776	0.199	0.0494	0	0.521
Density	21,767	313.9	1,987	0.194	67,139
Police (Arrest Power)	21,776	4.098	0.997	0	7.142
Police (Administrative)	21,776	3.562	1.337	0	8.302

Notes: Pawnshops, Banks and Savings Institutions and Police are standardized per 100.000 people, by county. Sources NACJD, US Census and Infogroup Academic (pawnshops only)

Table III: Control vs. Treated Baseline Characteristics

Variables	*(1) Control*	*(2) Treated*	*(3) Difference*
		Methamphetamines	
Meth-Labs seizures	*0.3*	*6.03*	*-5.73****
Meth-Hospitalizations	*20.43*	*67.3*	*-46.87****
		Theft Crimes	
Larceny	*1637.81*	*1913.75*	*-275.93****
Burglary	*478.22*	*642.25*	*-164.03****
Motor-Vehicle Theft	*211.08*	*207.3*	*3.78*
Robbery	*84.2*	*47.86*	*36.34****
		Violent Crimes	
Murder	*3.62*	*3.84*	*-0.22*
Assault	*228.37*	*238.82*	*-10.46*
Rape	*25.67*	*27.44*	*-1.76**
Arson	*22.29*	*17.99*	*4.29****
		Drugs-Related Arrests: Sale	
Cocaine	*54.37*	*29.42*	*24.95****
Marijuana	*28.88*	*32.66*	*-3.78***
Synthetic Narcotics	*4.84*	*13.06*	*-8.22****
Other Dangerous Non-Narcotics	*7.09*	*18.25*	*-11.16****
		Drugs-Related Arrests: Possession	
Cocaine	*93.18*	*59.38*	*33.79****
Marijuana	*272.48*	*219.41*	*53.08****
Synthetic Narcotics	*12.46*	*26.98*	*-14.51****
Other Dangerous Non-Narcotics	*28*	*51.77*	*-23.78****

Notes: Table III shows pre-intervention differences between Early Adopters and CMEA only states. It summarizes mean and differences of critical variables related to drugs and crime penetration in the two groups of states. Specifically, column (1) and (2) report the mean of each variable for CMEA only Early Adopters states. Column (3) shows the difference between (1) and (2), reporting 10%, 5% and 1% significance levels. Means are computed in the pre-intervention period – from 2001 to 2004 – with variables normalized per 100,000 inhabitants.

Table IVA – DD estimates: Early Adopters vs. CMEA Adopters
Burglary & Larceny

	(1)	*(2)* BURGLARY	*(3)*	*(4)*	*(5)* LARCENY	*(6)*
	Baseline	*+ County FE*	*+ County Observables*	*Baseline*	*+ County FE*	*+ County Observables*
*Treated * 2001*	*-0.0602*	*-0.0602*	*-0.0622*	*-0.0830*	*-0.0822*	*-0.0833*
	(0.0562)	*(0.0615)*	*(0.0649)*	*(0.0597)*	*(0.0653)*	*(0.0659)*
*Treated * 2002*	*-0.0366*	*-0.0364*	*-0.0379*	*-0.0772****	*-0.0767***	*-0.0776***
	(0.0390)	*(0.0427)*	*(0.0457)*	*(0.0283)*	*(0.0310)*	*(0.0326)*
*Treated * 2003*	*-0.0214*	*-0.0212*	*-0.0231*	*-0.0414*	*-0.0410*	*-0.0417*
	(0.0334)	*(0.0366)*	*(0.0374)*	*(0.0324)*	*(0.0356)*	*(0.0371)*
Treated * 2005	*-0.0788***	*-0.0788**	*-0.0808**	*-0.0944****	*-0.0944***	*-0.0975***
	(0.0358)	*(0.0391)*	*(0.0400)*	*(0.0326)*	*(0.0356)*	*(0.0393)*
Treated * 2006	*-0.116**	*-0.116**	*-0.110**	*-0.138***	*-0.138***	*-0.135***
	(0.0592)	*(0.0648)*	*(0.0607)*	*(0.0588)*	*(0.0643)*	*(0.0598)*
Observations	*9,824*	*9,824*	*9,800*	*9,824*	*9,824*	*9,800*
R-squared	*0.178*	*0.772*	*0.774*	*0.156*	*0.795*	*0.798*
Counties	*1,638*	*1,638*	*1,638*	*1,638*	*1,638*	*1,638*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
State FE	*YES*	*NO*	*NO*	*YES*	*NO*	*NO*
County FE	*NO*	*YES*	*YES*	*NO*	*YES*	*YES*
County Observables	*NO*	*NO*	*YES*	*NO*	*NO*	*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 outcome variable is burglary column (1) to (3) and larceny column (4) to (6). Outcome variables are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I use estimating equation (1). 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). Column (1) and (4) show the results for the baseline specification, where I include year FE and state FE. In column (2) and (5) I add to the baseline specification county FE. In column (3) and (6) 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 IVB - DD estimates: Early Adopters vs. CMEA Adopters
Crimes: Aggravated Assault & Murder

	(1)	(2)	(3)	(4)	(5)	(6)
		ASSAULT			MURDER	
	Baseline	+ County FE	+ County Observables	Baseline	+ County FE	+ County Observables
Treated * 2001	-0.0463	-0.0468	-0.0577	-0.0290	-0.0288	-0.0384
	(0.0569)	(0.0623)	(0.0627)	(0.0786)	(0.0860)	(0.0805)
Treated * 2002	-0.0537	-0.0534	-0.0629	-0.0655	-0.0649	-0.0755
	(0.0523)	(0.0572)	(0.0592)	(0.0611)	(0.0668)	(0.0679)
Treated * 2003	-0.00754	-0.00725	-0.0135	0.0624	0.0630	0.0455
	(0.0396)	(0.0433)	(0.0446)	(0.0642)	(0.0703)	(0.0719)
Treated * 2005	-0.0745	-0.0745	-0.0749	-0.164*	-0.164*	-0.162*
	(0.0442)	(0.0483)	(0.0501)	(0.0827)	(0.0905)	(0.0868)
Treated * 2006	-0.0696	-0.0696	-0.0545	-0.114	-0.114	-0.0779
	(0.0580)	(0.0634)	(0.0598)	(0.103)	(0.113)	(0.104)
Observations	9,824	9,824	9,800	9,824	9,824	9,800
R-squared	0.268	0.758	0.760	0.087	0.439	0.439
Counties	1,638	1,638	1,638	1,638	1,638	1,638
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	NO	NO	YES	NO	NO
County FE	NO	YES	YES	NO	YES	YES
County Observables	NO	NO	YES	NO	NO	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 outcome variable is aggravated assault column (1) to (3) and murder column (4) to (6). Outcome variables are expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants. I use estimating equation (1). 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). Column (1) and (4) show the results for the baseline specification, where I include year FE and state FE. In column (2) and (5) I add to the baseline specification county FE. In column (3) and (6) 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 V: Robustness Check DD Estimates

(1)	(2)	(3)	(4)
Larceny	Burglary	Assault	Murder
Panel A: Baseline			
-0.0975**	-0.0808*	-0.0749	-0.162*
(0.0393)	(0.0400)	(0.0501)	(0.0868)
-0.135**	-0.110*	-0.0545	-0.0779
(0.0598)	(0.0607)	(0.0598)	(0.104)
Panel B: Police			
-0.0952**	-0.0803**	-0.0741	-0.161*
(0.0383)	(0.0390)	(0.0509)	(0.0870)
-0.133**	-0.108*	-0.0536	-0.0768
(0.0599)	(0.0610)	(0.0600)	(0.104)
Panel C: State Linear Trends			
-0.123***	-0.122***	-0.149***	-0.250***
(0.0366)	(0.0396)	(0.0462)	(0.0833)
-0.194***	-0.199***	-0.209***	-0.252**
(0.0625)	(0.0697)	(0.0678)	(0.102)
Panel D: State Quadratic Trends			
-0.124***	-0.122***	-0.149***	-0.250***
(0.0370)	(0.0401)	(0.0455)	(0.0833)
-0.193***	-0.199***	-0.209***	-0.252**
(0.0625)	(0.0698)	(0.0682)	(0.102)
Panel E: Weighting by FBI Coverage Indicator			
-0.0916***	-0.0684*	-0.0690	-0.157*
(0.0310)	(0.0341)	(0.0431)	(0.0872)
-0.124**	-0.0914*	-0.0429	-0.0724
(0.0502)	(0.0533)	(0.0520)	(0.105)
Panel F: Excluding Mexico's Bordering States			
-0.106**	-0.0878*	-0.0806*	-0.187**
(0.0468)	(0.0469)	(0.0559)	(0.0856)
-0.135*	-0.110	-0.0585	-0.0879
(0.0682)	(0.0687)	(0.0688)	(0.104)
Panel G: Including the State of Kentucky			
-0.107**	-0.0887**	-0.0830	-0.175*
(0.0435)	(0.0427)	(0.0499)	(0.0876)
-0.173**	-0.145*	-0.0829	-0.104
(0.0782)	(0.0774)	(0.0689)	(0.108)

*Notes: This table shows the robustness checks for estimating equation (1). Column (1) reports the results for larceny, column (2) for burglary, column (3) for aggravated assault and column (4) for murder. From panel A to H I only report the coefficients of the interactions between the indicator variables "treated" * "year 2005" (first row) and "treated" * "year 2006" (second row). In order to allow an easier comparison, Panel A reports the results obtained using estimating equation (1) that includes state FE, year FE and all county-level controls. Panel B shows the results when I add to the baseline specification both the measures of police officers with arrest powers and civilian employees. Panel C and panel D reports the results including state specific-linear trends and state-specific quadratic trends, respectively. Panel E 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. Panel F shows the results when I exclude counties belonging to California, Arizona and Texas, three early adopters states sharing the borders with Mexico, the larger supplier of methamphetamines in the United Stated via Mexican cartels. In Panel G I show the results including in the analysis the state of Kentucky, an early adopter state for which crimes information are extremely imprecise, with more than 40% of cases where crime is not reported at all (FBI coverage indicator equals zero).*

Table VI - Meth-Labs Seized by Law Enforcement Agencies

	(1) Baseline	(2) + County FE	(3) + County Observables	(4) + Police
Treated * Post	-0.414***	-0.414***	-0.372***	-0.372***
	(0.0788)	(0.0961)	(0.0811)	(0.0807)
Observations	4,914	4,914	4,896	4,896
R-squared	0.279	0.693	0.696	0.696
Counties	1,636	1,636	1,636	1,636
Year FE	YES	YES	YES	YES
State FE	YES	NO	NO	NO
County FE	NO	YES	YES	YES
County Observables	NO	NO	YES	YES
Police	NO	NO	NO	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 county – year. This table reports the results of a difference in differences specification. The outcome variable is the number of meth-labs seized by law enforcement agencies and it expressed as ln(1+x) where x is the number of labs per 100,000 inhabitants. Data on labs are available from 2004 onwards. 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) with the POST dummy (years 2005 and 2006). I consider as control counties, counties in States that only adopted the CMEA federal law (the last provision of the law took effect the 30th of September 2006. Column 1 shows the results for the baseline specification, when I include year FE and state FE. In column 2 I add to the baseline specification county FE. In column 3 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. In column 4 I add, sworn law enforcement officers and civilians.*

Table VII: Meth Trafficking and Associated Systemic Violence

	(1) Arrests for Sale	*(2) Arrests for Sale (State Linear Trends)*	*(3) Gangs & Trafficking Violence*
*Treated * 2001*	*-0.406****	*-0.264**	*-0.0487*
	(0.143)	*(0.140)*	*(0.0433)*
*Treated * 2002*	*-0.155*	*-0.0652*	*0.0124*
	(0.129)	*(0.108)*	*(0.00822)*
*Treated * 2003*	*0.00711*	*0.0420*	*-0.00475*
	(0.0894)	*(0.0933)*	*(0.0121)*
Treated * 2005	*-0.0508*	*-0.0899*	*-0.00811*
	(0.115)	*(0.112)*	*(0.0170)*
Treated * 2006	*-0.230**	*-0.305***	*0.00209*
	(0.128)	*(0.122)*	*(0.0155)*
Observations	*9,800*	*9,800*	*9,800*
R-squared	*0.663*	*0.677*	*0.202*
Counties	*1,636*	*1,636*	*1,636*
Year FE	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*
State Linear Trends	*NO*	*YES*	*No*

*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 (1). 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). Col (1) shows the results of arrests for sale of other dangerous non-narcotics, the FBI category including crystal methamphetamines. In column (2) I add state-linear trends. Column (3) shows the results for murders due to gangs and drug trafficking. Outcome variables are all expressed as ln(1+x), where x is the crime measure normalized per 100,000 inhabitants*

Table VIII: Meth-related Arrests for Possession and Hospitalization

	(1) *Arrests for Possession of Meth*	*(2)* *Hospitalization due to Meth Abuse*
*Treated * 2001*	*-0.266*	*-0.11*
	(0.235)	*(0.28)*
*Treated * 2002*	*0.0492*	*-0.06*
	(0.196)	*(0.25)*
*Treated * 2003*	*0.00357*	*0.05*
	(0.0886)	*(0.19)*
Treated * 2005	*0.129*	*0.28*
	(0.0975)	*(0.28)*
Treated * 2006	*-0.0743*	*0.04*
	(0.151)	*(0.31)*
Observations	*9,800*	*224*
R-squared	*0.744*	*0.87*
Counties	*1,636*	*-*
Year FE	*YES*	*YES*
County FE	*YES*	*-*
State FE	*-*	*YES*
County Observables	*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 (1). 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). Col (1) shows the results of arrests for possession of other dangerous non-narcotics, the FBI category including crystal methamphetamines. In column (2) I report the results for hospitalization due to meth abuse. Outcome variables are all expressed as ln(1+x), where x is the outcome variable normalized per 100,000 inhabitants.*

TABLE IX-A
Meth-Labs & Theft Crimes

	(1)	(2)	(3)	(4)	(5)	(6)
	Larceny		Burglary		M/V Theft	
	OLS	IV	OLS	IV	OLS	IV
Seized Meth-Labs	0.0876***	0.268***	0.0666***	0.245***	0.0880***	0.114
	(0.0201)	(0.0640)	(0.0177)	(0.0666)	(0.0188)	(0.0747)
Observations	4,896	4,896	4,896	4,896	4,896	4,896
R-squared	0.193	0.174	0.184	0.162	0.270	0.270
Counties	1,636	1,636	1,636	1,636	1,636	1,636
F-statistic	-	104.5	-	104.5	-	104.5
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
County 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 county – year. This table reports the results of both the OLS and IV specification for Larceny, Burglary and Motor-Vehicle Theft. The endogenous variable is the number of meth-labs seized by law enforcement agencies. I use as instrument 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) with the "POST" dummy (years 2005 and 2006). I consider as control counties, counties in States that only adopted the CMEA federal law (the last provision of the law took effect the 30th of September 2006 Outcome variables and meth-labs are expressed as ln(1+x) where x is the relevant measure per 100,000 inhabitants. Data on labs are available from 2004 onwards. The specification include year FE, state FE and all 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 IX-B

Meth-Labs & Violent Crimes

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	Rape		*Assault*		*Murder*	
	OLS	*IV*	*OLS*	*IV*	*OLS*	*IV*
Seized Meth-Labs	*0.0685****	*0.347***	*0.0487****	*0.200****	*0.0167*	*0.353***
	(0.0212)	*(0.136)*	*(0.0177)*	*(0.0707)*	*(0.0175)*	*(0.145)*
Observations	*4,896*	*4,896*	*4,896*	*4,896*	*4,896*	*4,896*
R-squared	*0.196*	*0.156*	*0.300*	*0.285*	*0.147*	*0.055*
Counties	*1,636*	*1,636*	*1,636*	*1,636*	*1,636*	*1,636*
F-statistic	*-*	*104.5*	*-*	*104.5*	*-*	*104.5*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
State FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County 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 county – year. This table reports the results of both the OLS and IV specification for rape, aggravated assault and murder. The endogenous variable is the number of meth-labs seized by law enforcement agencies. I use as instrument 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) with the "POST" dummy (years 2005 and 2006). I consider as control counties, counties in States that only adopted the CMEA federal law (the last provision of the law took effect the 30th of September 2006. Outcome variables and meth-labs are expressed as ln(1+x) where x is the relevant measure per 100,000 inhabitants. Data on labs are available from 2004 onwards. The specification include year FE, state FE and all 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.*

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Table X - Meth-Labs & Crime - IV Estimates with County FE

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Theft Crimes			*Violent Crimes*	
	Larceny	*Burglary*	*M-V Theft*	*Murder*	*Assault*	*Rape*
Seized Meth-Labs	*0.299****	*0.247****	*0.129*	*0.342***	*0.150**	*0.353***
	(0.0754)	*(0.0782)*	*(0.0811)*	*(0.164)*	*(0.0820)*	*(0.157)*
Observations	*4,890*	*4,890*	*4,890*	*4,890*	*4,890*	*4,890*
Number of counties	*1,630*	*1,630*	*1,630*	*1,630*	*1,630*	*1,630*
F-statistic	*83.8*	*83.8*	*83.8*	*83.8*	*83.8*	*83.8*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County 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 county – year. This table reports the results of the IV specification for Larceny, Burglary, Motor and Vehicle Theft, Murder, Aggravated Assault and Rape with county FE. The endogenous variable is the number of meth-labs seized by law enforcement agencies. I use as instrument 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) with the "POST" dummy (years 2005 and 2006). I consider as control counties, counties in States that only adopted the CMEA federal law (the last provision of the law took effect the 30th of September 2006. Outcome variables and meth-labs are expressed as ln(1+x) where x is the relevant measure per 100,000 inhabitants. Data on labs are available from 2004 onwards. The specification include year FE, county FE and all 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 XI - Homicide Circumstances

Type of Crime	*Frequency*	*Percent*
Theft-Crimes		
Robbery	*6,747*	*6.61*
Burglary	*567*	*0.56*
Larceny	*103*	*0.1*
Motor vehicle theft	*160*	*0.16*
Sex-Crimes		
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 Crimes		
Narcotic drug offense	*4,189*	*4.1*
Gangland killings	*614*	*0.6*
Juvenile gang killings	*5,454*	*5.34*
Violent Crimes		
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*
Crime due 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: Source NAJCD 2001-2006

Table XII Anti-Meth Legislation, Homicide Circumstances and Hate Crimes

	(1) Theft	(2) Sex	(3) Gangs & Drug Trafficking	(4) Gangs & Brawls & Arguments	(5) Negligence	(6) Hate Crimes
*Treated * 2001*	0.0432**	0.0196	-0.0487	-0.0827**	0.00107	-0.04
	(0.0211)	(0.0249)	(0.0433)	(0.0388)	(0.0137)	(0.09)
*Treated * 2002*	0.000910	0.0291*	0.0124	0.00600	-0.0168	-0.04
	(0.0272)	(0.0159)	(0.00822)	(0.0444)	(0.0165)	(0.09)
*Treated * 2003*	0.0435*	0.0192	-0.00475	-0.00498	0.0110	-0.15**
	(0.0235)	(0.0244)	(0.0121)	(0.0676)	(0.0146)	(0.07)
Treated * 2005	0.00437	0.0126	-0.00811	-0.0828*	0.00979	0.10**
	(0.0217)	(0.0187)	(0.0170)	(0.0420)	(0.0143)	(0.05)
Treated * 2006	-0.0338	0.000534	0.00209	0.0151	-0.00460	-0.05
	(0.0340)	(0.0155)	(0.0155)	(0.0300)	(0.00894)	(0.08)
Observations	9,800	9,800	9,800	9,800	9,800	9,800
R-squared	0.274	0.181	0.202	0.233	0.174	0.288
Counties	1,636	1,636	1,636	1,636	1,636	1636
Year FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
County 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 county – year. This table reports the results of the difference in differences specification with a different outcome for each column. I include the following categories of homicides circumstances: theft, sex, gangs and drug trafficking, brawls and arguments, negligence and hate crimes. Outcome variables are expressed as ln(1+x) where x is the relevant measure per 100,000 inhabitants. 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) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). I exclude from the estimation the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws). I include year FE, county FE and 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 XIII Hate Crimes by Type of Motivation

Motivation	*Frequency*	*%*
Anti-Black	*15,306*	*34.5*
Anti-Jewish	*5,071*	*11.43*
Anti-White	*4,611*	*10.39*
Anti-Male-Homosexual	*4,330*	*9.76*
Anti-Other-Ethnicity	*3,811*	*8.59*
Anti-Hispanic	*3,000*	*6.76*
Anti-Homosexual (both)	*1,267*	*2.86*
Anti-Asian	*1,249*	*2.81*
Anti-Islamic	*1,170*	*2.64*
Anti-Multi-Racial	*1,088*	*2.45*
Anti-Female-Homosexual	*977*	*2.2*
Anti-Other-Religion	*743*	*1.67*
Anti-Am-Indian	*402*	*0.91*
Anti-Catholic	*329*	*0.74*
Anti-Protestant	*271*	*0.61*
Anti-Multi-Religious	*229*	*0.52*
Anti-Mental-Disability	*169*	*0.38*
Anti-Physical-Disability	*115*	*0.26*
Anti-Heterosexual	*114*	*0.26*
Anti-Bisexual	*89*	*0.2*
Anti-Atheism/Agnosticism	*30*	*0.07*
Total	*44,371*	*100*

Note: this table shows the distribution of hate crimes by type of motivating bias. Source NACJD (2001 – 2006).

Table XIV - Spillover Effects Across Drugs (Possession and Sale)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Possession			*Sale*	
	Synthetic	*Marijuana*	*Cocaine*	*Synthetic*	*Marijuana*	*Cocaine*
*Treated * 2001*	*-0.207*	*-0.288*	*-0.275***	*-0.239*	*-0.296**	*-0.126*
	(0.191)	*(0.176)*	*(0.108)*	*(0.177)*	*(0.150)*	*(0.113)*
*Treated * 2002*	*-0.0749*	*-0.0242*	*-0.0687*	*0.0358*	*-0.123*	*0.0003*
	(0.147)	*(0.0753)*	*(0.0895)*	*(0.127)*	*(0.0896)*	*(0.0766)*
*Treated * 2003*	*-0.228*	*0.0371*	*-0.109*	*0.0357*	*0.0755*	*0.0576*
	(0.145)	*(0.0672)*	*(0.0716)*	*(0.115)*	*(0.0763)*	*(0.0621)*
Treated * 2005	*-0.0132*	*0.0772*	*-0.0259*	*-0.0975*	*-0.0656*	*-0.067*
	(0.0901)	*(0.0805)*	*(0.0678)*	*(0.0803)*	*(0.0676)*	*(0.0836)*
Treated * 2006	***-0.133***	*0.0696*	*0.111*	***-0.196***	*0.0298*	*-0.0506*
	(0.112)	*(0.0787)*	*(0.124)*	***(0.140)***	*(0.118)*	*(0.0853)*
Observations	*9,800*	*9,800*	*9,800*	*9,800*	*9,800*	*9,800*
R-squared	*0.762*	*0.833*	*0.827*	*0.669*	*0.668*	*0.756*
Counties	*1,636*	*1,636*	*1,636*	*1,636*	*1,636*	*1,636*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County 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 county – year. This table reports the results of the difference in differences specification with a different outcome for each column. Using the FBI categorization I include synthetic Narcotics (manufactured narcotics that can cause true drug addiction), Marijuana and Cocaine, Opium or Derivatives. Outcome variables are expressed as ln(1+x) where x is the relevant measure per 100,000 inhabitants. 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) 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 include year FE, county FE and 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 XV - Table Anti-Meth Legislation & Crime's Geographical Spillovers

	(1) Seized Meth-Labs	*(2) Larceny*	*(3) Burglary*	*(4) Assault*	*(5) Murder*
*Neighboring county * 2001*		*0.104**	*0.106**	*0.195****	*0.275*
		(0.0606)	*(0.0600)*	*(0.0736)*	*(0.211)*
*Neighboring county * 2002*		*-0.0206*	*0.00590*	*0.0782*	*0.0285*
		(0.0332)	*(0.0411)*	*(0.0560)*	*(0.140)*
*Neighboring county * 2003*		*0.0137*	*0.0465*	*0.0183*	*-0.107*
		(0.0249)	*(0.0355)*	*(0.0433)*	*(0.139)*
Neighboring county * 2005	*0.0776*	*-0.0183*	*-0.0414*	*0.0482*	*0.0364*
	(0.104)	*(0.0189)*	*(0.0372)*	*(0.0560)*	*(0.160)*
Neighboring county * 2006	*-0.0182*	*-0.0168*	*-0.00997*	*0.0517*	***0.230***
	(0.0763)	*(0.0339)*	*(0.0458)*	*(0.0611)*	***(0.144)***
Observations	*414*	*827*	*827*	*827*	*827*
R-squared	*0.569*	*0.861*	*0.868*	*0.922*	*0.602*
Counties	*1,636*	*1,636*	*1,636*	*1,636*	*1,636*
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. The level of observation is county – year. This table reports the results of a difference in differences specification with a different outcome variable for each column. Meth-labs seized by police, larceny, burglary, aggravated assault and murder are expressed as ln(1+x) where x is the number of crimes per 100,000 inhabitants. I interact the variable "Neighboring County" (a dummy taking the value of 1 if the county belongs to a CMEA only state and it shares the borders with a county in a treated state) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). I keep in the estimation only counties in CMEA only states. I exclude from the estimation the interaction between the dummy treated and the dummy for the year 2004 (the year before the enactment of the states laws). I include year FE, county FE and 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.*