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DECLARATION

I declare that the material contained in this thesis has not been used or published before. This thesis is my own work and it has not been submitted for another degree or at another university.

Rocco d'Este

Chapter I – Black Markets and Crime

I. Introduction

Since Becker's seminal work (1968), economists have investigated the determinants of crime using of a cost-benefit analysis. But, while extensive research has focused on incentives related to sanctions, deterrence and legal labor market opportunities, the effects of Black Markets (i.e. markets in which goods and services are illegally traded) on crime have been generally overlooked.

Two main obstacles have hindered such an analysis. First, black markets are by definition clandestine. Hence, these are very hard to measure. Secondly, these markets are not randomly assigned to geographic locations, but rather endogenously located, following existing economic trends or cross-sectional area characteristics.

This PhD thesis aims to partially fill this gap. I investigate the effects on criminal activity of 1) markets for stolen goods and 2) markets for illegal drugs.

I start by focusing on pawnshops, widespread legal markets often associated with the illicit trade of stolen property. I build a novel panel dataset of 2,200 US counties (94 % of US population coverage). I match FBI information to pawnshops' presence. Within-county estimates reveal that a one-standard-deviation increase in the number of pawnshops is associated with 0.05 to 0.1 standard deviation increase in property thefts. Falsification tests add support for the hypothesis of the paper: the correlation between pawnshops and crime is only isolated to the case of property thefts. Motor-vehicle thefts are unaffected, plausibly because these shops do not accept this type of item. No effect is ever

detected on any other violent crime, such as murders, aggravated assaults and rapes.

To address reverse causality issues, I then use a quasi-experimental design. I show that the effects of rising gold prices on burglaries are amplified by the predetermined prevalence of these businesses within a county. The analysis suggests that pawnshops increase the expected benefits from crime by providing a deeper market for stolen goods.

The rest of the PhD thesis investigates the effects of illegal drugs markets on crime. I focus on crystal methamphetamines, one of the most dangerous drugs in the United States. I use as a source of exogenous variation Over-the-Counter (OTC) restrictions to meth's critical inputs of production. Heavy crystal-meth addicts typically produce this substance in clandestine "home-labs", mainly to sustain their habit. Several quasi-experimental designs are performed on a newly assembled panel dataset. This unveils the interlinkages between drugs and criminal activity due to a unique combination of Drugs Enforcement Agency (DEA) and FBI county-level information.

Chapter III investigates the direct effect OTC restrictions on crime. A difference-in differences (DD) design shows that OTC restrictions led to a decline of 5% to 10% in both property and violent crimes. The effects of the law are stronger (i.e. more negative) in rural counties where – typically – meth production and abuse takes place. This chapter also shows a variety of robustness checks and placebo tests.

Chapter IV investigates the mechanisms behind the reduction in crime. I detect a 38% drop in operating meth-labs, driven by small-medium quantity labs. I do not detect strong signs of relocation of criminal activity across states' borders, substitution in the demand or supply of other illegal substances, crackdown of police on meth-abusers.

I then propose a simple theoretical framework that matches qualitative features of this clandestine market. I model the decision process of a typical "meth-head" hit by OTC restrictions via an unexpected crystal-meth price-shock. This framework guides and sharpens the interpretation of the results, providing an additional set of testable predictions. These are corroborated by the subsequent empirical analysis or by further descriptive/qualitative evidence. OTC restrictions led to: i) a drop in meth consumption, ii) an increase in voluntary meth-related hospitalizations associated with detox, withdrawal symptoms and rehab, iii) heterogeneous and non-monotonic effects on criminal activity across US states.

Chapter V aims to estimate the effect of the opening/closing or entry/exit of an additional meth-lab on crime. I use a combination of diff-in-diff and IV designs. First, I present the baseline empirical strategy and the related results. Then, I discuss potential threats to identification, proposing and implementing alternative approaches with the scope of reducing concerns related to the violation of the exclusion restriction. I detect an elasticity of both property and violent crimes to meth-labs in the range of .1 to.3. Finally, I also present: i) an additional DD design exploiting a subsequent federal act, ii) the examination of the long-run effects of OTC restrictions on crime.

Overall, this work supports the hypothesis that OTC regulations "capped the meth-epidemic", slowing-down the spiral of heavy drugs' abuse and associated criminal behavior soaring "under the influence" of this powerful substance. Ultimately, this thesis suggests that including in Becker "cost-benefit" framework (1968) the direct criminogenic effects arising from drug abuse, might lead to a deeper understanding of criminal behavior's production function.

Chapter II – The Effect of Stolen Goods Markets on Crime: Pawnshops, Property Thefts and the Gold Rush of the 2000s

By ROCCO D'ESTE

This chapter investigates the effects of stolen goods markets on crime. I focus on pawnshops, assembling a novel dataset encompassing 2,200 US counties from 1997 to 2010. Within-county estimates reveal that a one-standard-deviation increase in the number of pawnshops is associated with 0.05 to 0.1 standard deviation increase in property thefts. Using a quasi-experimental design, I then show that the effects of rising gold prices on burglaries are amplified by the predetermined prevalence of these businesses within a county. This suggests that pawnshops increase the expected benefits from crime by providing a deeper market for stolen goods.

I. Introduction

Theft crimes represent a substantial social cost to society. In 2010, the United States experienced one theft every 40.5 seconds, with a total of 9.5 million crimes and an estimated economic loss for victims of almost $16 billion (FBI, 2010)[1]. Personal items were stolen in almost 85 percent of cases, strongly suggesting that burglars need a market in which to convert these goods into cash (Walters et al., 2013). In particular, this raises the hypothesis that the local availability of stolen goods markets may affect criminal behavior by reducing theft-related *transaction costs* and by raising the *expected benefits* deriving from illegal activity (Sutton, 2010).

Since Becker's seminal work (1968), economists have investigated the determinants of crime using of a cost-benefit analysis. But, while extensive research has focused on incentives related to sanctions, deterrence and legal labor

[1] http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/offenses-known-to-law-enforcement/standard-links/national-data

market opportunities,[2] the effects of stolen good markets on crime have been generally overlooked. Two main obstacles have hindered such an analysis. First, markets for stolen property are by definition clandestine and – hence – very hard to measure. Secondly, these markets are not randomly assigned to geographic locations, but rather endogenously located, following existing economic trends or cross-sectional area characteristics.

This paper contributes to the existing literature on crime by analyzing this issue through the channel of *pawnshops*, widespread legal markets often associated with the illicit trade of stolen property. I build a novel panel crime-related dataset, collecting information on 8 reported crimes and on the number of pawnshops for 2,200 US counties in 50 states, from 1997 to 2010. I hence focus on the effects that these businesses have on the proliferation of illegal activity.

I address endogeneity concerns in multiple ways. First, I use a fixed effects framework, including in the analysis a wide set of county, time-varying, socio-economic controls.[3] Then, I exploit the rise of gold prices as a quasi–natural experiment, interacting gold prices with the initial concentration of pawnshops in a county, *fixed to the first year of the sample*. The hypothesis is that shifts in the resale value of gold will cause more property thefts in counties with a higher concentration of businesses that generate a big part of their profits by trading gold products such as rings, necklaces and bracelets.

In the first part of the paper I rely on within-county variation in the number of pawnshops to explain within-county variation in the number of reported crimes. Ordinary least square estimates reveal a significant effect of these businesses on two theft-crimes: larceny and burglary. A marginal increase of pawnshops in a county is associated with 6 more property thefts in the same county. The

[2] See Chalfin and McCrary (2013) for a detailed literature review.

[3] Please refer to the "Data and Empirical Analysis" section for a detailed description of all controls used in the analysis.

magnitude of the results is larger if I consider the presence of geographical spillovers: one pawnshop more in a state is associated with 36 more property thefts in a county belonging to the same state. To put these results into perspective, a one-standard-deviation increase in the number of pawnshops is associated with 0.05 to 0.1 standard deviation increase in property thefts.

These findings are robust to extensive checks, such as the clustering of standard errors at different levels, sensitivity analysis with respect to outliers, weighting the regression by a measure of the quality of the information on reported crimes and excluding from the sample highly populated counties.

Falsification tests add support for the hypothesis of the paper: in fact, the correlation between pawnshops and crime is only isolated to the case of property thefts. In particular, motor-vehicle thefts are unaffected, plausibly because these shops do not accept this type of item. Moreover, no effect is ever detected on any other violent crime, such as murders, aggravated assaults and rapes.

The lack of random assignment poses two different threats to the identification of a causal parameter. First, results might be driven by the omission of confounding county-specific and time-varying unobservables. Nevertheless, the coefficients of interest are almost unaffected by the inclusion of 18 socio-economic controls, reducing concerns that selection on unobservables is mainly driving the results.

The second econometric concern is related to the bias arising due to reverse causality: increases in property thefts may lead to the opening of additional pawnshops. I address this issue in the last section of the paper, by introducing the interaction between gold prices and the concentration of pawnshops in a county, fixed to the first year of the sample.

Gold is the major source of pawnbrokers' business, representing a high percentage of the value of all pledges (Bos et al, 2012). The demand for gold materializes through trade in jewelry, which is frequently melted down by

pawnbrokers through a "refinement" process. During this process, professional outfits remove impurities from metal until they get a metal that is closer to being pure gold and, therefore, cannot be traced when re-sold. In this way, stolen jewelry can disappear forever via the counters of pawnshops.

The empirical analysis shows that a one standard deviation increase in the initial concentration of pawnshops in a county increases the effect of gold prices on burglaries by 0.05 to 0.10 standard deviations, with no effect detected on motor-vehicle thefts or any other crimes.

I then include in the analysis the interaction between each socio-economic county observable – fixed at the first year of the sample – and gold prices. This specification attempts to control for other confounding channels through which the rise of gold prices might have affected the proliferation of burglaries, with different trends in different counties. Results are robust to this and to other specifications. Overall, the analysis supports the hypothesis that these businesses can amplify the expected benefits of thefts by providing a deeper market for stolen goods.

As a final falsification test, I include the interaction between the initial concentration of pawnshops and copper prices, without detecting any positive effect on burglaries. This is consistent with the fact that pawnshops do not commonly trade copper, even if criminals heavily target objects made with this metal. The resale market for copper is indeed more heavily concentrated around dedicated scrap metal dealers.[4]

The results in my empirical analysis are important both for researchers and policy makers.

From a research perspective, this paper contributes to the existing literature on crime in two novel ways. First, this is one the first investigation of the effects of

[4] See Sidebottom (2011), or Cardoso et al (2013).

stolen goods markets on criminal activity.[5] This paper is hence closely related to an unpublished PhD dissertation chapter by Thomas J. Miles (2007), who finds a positive effect of pawnshops on crime on a cross section of US counties, in the year 1996. He addresses endogeneity issues using state-level variation in the maximum interest rate allowed to pawnbrokers, an interesting approach nevertheless characterized by some data limitations.[6]

Second, this is one of the first papers that analyses the effects of a change in *crime's expected benefits*, exploiting the rise in gold and copper prices as a quasi-natural experiment. This work is hence closely related to Draca, Koutmeridis and Machin (2014). Their findings support the hypothesis that crimes are highly responsive to consumer and scrap metal prices, suggesting that, as potential takings from thefts rise with prices, criminals switch into crimes that yield a higher return.

From a policy perspective, these findings suggest the need for a closer monitoring of these shops by local authorities. This monitoring, by reducing the latent demand for stolen properties, should reduce the supply of crime in pawnshops' proximity. This is in line with the decision of some municipalities in the Unites States to apply stricter rules on this business, increasing the penalties in

[5] Different studies have analysed a wide set of crime's potential determinants. Among these: the effect of police and incarceration (Levitt 1997, Di Tella and Schargrodsky 2004, Klick and Tabarrok 2005, Levitt 1996, Levitt 1998, Helland and Tabarrok 2007, Drago, Galbiati and Vertova 2009, Lee and McCrary 2009, Draca, Machin and Witt 2011), conditions in prisons (Katz, Levitt and Shustorovich 2003), parole and bail institutions (Kuziemko 2007), education (Western, Kling and Weiman 2001, Lochner and Moretti 2004), social interactions and peer effects (Case and Katz 1991, Glaeser, Sacerdote and Scheinkman 1996, Gaviria and Raphael 2001, Kling, Ludwig and Katz 2005, Jacob and Lefgren 2003, Bayer, Hjalmarsson and Pozen 2009), family circumstances (Glaeser and Sacerdote 1999, Donohue and Levitt 2001). Economists have also focused on the effect of criminal histories on labour market outcomes (Grogger 1995, Kling 2006), the impact of unemployment and wages on crime (Grogger 1998, Raphael andWinter- Ebmer 2001), the strategic interplay between violent and property crime (Silverman 2004), the optimal law enforcement (Polinsky and Shavell 2000, Eeckhout, Persico and Todd 2009), the immigration status (Bianchi, Buonanno and Pinotti 2012), the impact of violent movies and pornography on violent crimes (Dahl and Della Vigna 2009 and Bhuller, Havnes, Leuven and Mogstad 2011).

[6] In particular, the analysis is limited to only one year of data (1996). This, along side the use of a state-level instrument, does not allow for the inclusion of county nor state fixed-effects. In practice, any county/state unobservable characteristics, related to the number of pawnshops, crime and the state's decision of setting a particular interest rate might be a confounding factor in the analysis.

case of poor documentation of all transactions made by pawnbrokers.[7] For these reasons, new policies are being implemented. These measures require pawnbrokers to share their records with authorities on a daily basis, using a free online reporting system, including jewelry and used electronic goods that can be tracked by serial numbers.[8]

More broadly, this study highlights the scope to further investigate, separate and quantify the effects that other potential markets such as junkyards, flea markets, EBay, Craigslist and the dark web could have on the proliferation of illegal activity.[9] In fact, these and other markets may affect criminals' incentives by reducing theft-related transaction costs, by increasing the expected benefits from thefts, by amplifying the effects of world prices fluctuations of metals and technological goods and – in some cases – by selling weapons, illicit drugs and other illegal products.[10] These and other interesting aspects are hence left for future research.

This paper unfolds as follows. Section II provides some institutional background on pawnshops. Section III presents the data and lays out the initial econometric framework, it reports the findings for that framework and provides various robustness checks and heterogeneity in the results. Section IV introduces the role of gold in the quasi-natural experiment, outlines the research design and presents the results. Section V concludes.

[7] See the next section for more background information on pawnshops' regulation.

[8] See for example: http://www.statesman.com/news/news/local/plan-would-require-some-secondhand-stores-to-sha-1/nRkKz/?__federated=1 or http://thetimes-tribune.com/news/scranton-to-require-stricter-rules-for-pawn-shops-1.1658773

[9] See FBI report on the dark web: http://www.fbi.gov/news/podcasts/thisweek/the-dark-web.mp3/view

[10] See for example: http://www.zdnet.com/article/beyond-silk-road-2-0-over-400-dark-web-tor-sites-seized-by-fbi/

II. Institutional Background

Pawnshops, payday loans and check-cashing outlets are all businesses that provide credit to "unbanked" clients at very high interest rates.[11] Among these activities, pawnbrokers offer a unique service: they supply instant cash in exchange for taking physical possession of the client's personal property.

The standard procedure begins with an assessment of the monetary value of the client's item. If the client accepts the offer, she can either directly sell the item to the pawnbroker or she can ask for a loan, using the pledge as a collateral. Usually, the offer ranges from 30 to 75 per cent of the market value of the pledge, with the average loan value being $100. The pawnbroker holds the personal item in custody until the maturity date of the loan, typically two months later. If the client does not return to reclaim the pledged item, ownership of the item passes to the pawnbroker.[12]

Several dynamics can turn a pawnshop into a market for stolen goods (Sutton, 2010). First of all, even if pawnbrokers assume the risk that an item might have been stolen, they often only loose the collateral and the amount loaned in case where the police seize the item.[13] Competition may also reduce a pawnbroker's incentive to question items of uncertain origin. As one pawnbroker put it: "*If he's coming in my store with a VCR, I'm not asking him where he got it. It's the police's job to find out if it's stolen, not mine. You don't ask where things come*

[11] U.S. households purchased more than $40 billion in high-cost short-term loans using the "fringe banking sector" in 2007, Fellowes and Mabanta (2008). Even if there is no official and reliable estimate of the total number of clients, industry reports suggest that 34 million adults demanded the services of these companies. The sector consists of several types of high-cost lenders, but two comprise the dominant portion: payday lenders and pawnshops. In 2007 pawnshops made 42 million transactions for an overall value of 2.5 billion dollars. The maximum interest rate set by pawnbrokers and payday lenders is generally regulated at the state level. For a complete review of pawnshops' operating system see Shackman and Tenney (2006).

[12] Alternatively, the pawnbroker becomes the owner of the item as soon as the sale process ends. About 80 per cent of pawn loans are repaid and repeat customers account for much of the loan volume. Moreover, it is common for a customer to use the same pledge as collateral to obtain sequential loans (Avery, 2011).

[13] The charge for criminal possession depends on the evidence of the pawnbroker being aware of the illegal origin of the item, a fact that is usually very difficult to establish. See for example: http://www.lacriminaldefenseattorney.com/Legal-Dictionary/F/FA-FIRE/Fence.aspx

from. If you don't take those, the guy down the street will" (Glover and Larubbia, 1996). Finally, the pawnbroker could explicitly facilitate the sale of stolen goods in his shop (fencing),[14] exploiting the lack of strict law enforcement from local authorities or, for example, the fact that most stolen goods lack of a unique identifier and are hard to recognize by police or by the victims.[15]

For all these reasons, laws in many jurisdictions strictly regulate pawnbrokers' activities. These laws usually require a photo identification of the client (such as a driver's license or government-issued identity document), as well as a "holding" period on the item purchased by the pawnbroker, to allow local law enforcement authorities to track stolen items. Pawnshops must also regularly send to police a list of all newly pawned items and, if possible, any associated serial number.

Despite the existence of these laws, various investigative reports add support to the hypothesis of a close link between pawnshops and criminal activity. Glover and Larrubia used the pawnshops-level transaction data to rank pawnshops clients by the number of transactions made in 1996. Thirty-nine of the top fifty clients had criminal arrest records, often related to burglary, theft, or related offenses.[16]

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[14] Police efforts have indicated that some pawnbrokers are involved in fencing. For example, in the US, the Sarasota Police Department, Venice Police Department and North Port Police Department assisted with the undercover operation to sell gold jewelry to each business. Many were found to be in compliance. However, a number of businesses operated under a 'no questions asked' policy, making no attempt to properly document the seller information, record the items being purchased or obtain the seller's fingerprint (Bill, 2011).

[15] Wright and Decker (1994) interviewing burglars in the St. Louis area, describe different mechanisms through which pawnshops may be used to quickly convert stolen goods into cash. First, even if a burglar must provide his name, address, and a form of identification, jurisdictions rarely make full use of this information. Moreover, these requirements can be easily deceived. The burglar may provide false information (Glover and Larrubia, 1996) or use false identification when needed. Alternatively, some burglars reported persuading friends to pawn the items for them, reducing the likelihood that a pawnbroker would not accept the item from a suspicious client (Wright and Decker, 1994). Finally, jewelry such as rings, bracelets and necklaces can easily be melted down, transforming forever stolen items into unrecognizable bars of precious metal (Sutton, 2010).

[16] In a subsequent study Wallace (1997) describes how pawnshops may enable few highly motivated criminals to commit many offenses. For example, an unemployed man visited a single pawnshop 38 times in less than two months and pawned, among other items, thirteen women's rings, ten men's rings, eleven necklaces, nine cameras, six watches, three VCRs, and two televisions. The day after his last visit to the pawnshop, the man was arrested for burglary. Another police survey of frequent pawners produced like findings in Portland, Oregon. 90 per cent of these pawners were chronic drug users with long criminal records (Hammond 1997).

Fass and Francis (2005) used a similar approach to analyze a database of all pawn transactions recorded by the Dallas Police Department (DPD) during the six-year period from January 1, 1991, through December 31, 1996.[17] The 14,500 people pawning 30 times or more during the period "*were two to three times more likely to have been convicted for theft, larceny, burglary, or robbery than those who pawned once or twice.*"[18]

Overall, this evidence points towards pawnshops being a major channel for the intermediation of stolen goods.

III. Data and Empirical Analysis

Pawnbrokers have often been associated with fencing. While pawnbrokers do not like this characterization of their business, police efforts have indicated that some pawnbrokers are involved in fencing. For example, in the US, the Sarasota Police Department, Venice Police Department and North Port Police Department assisted with the undercover operation to sell gold jewelry to each business. Many were found to be in compliance. However, a number of businesses operated under a 'no questions asked' policy, making no attempt to properly document the seller information, record the items being purchased or obtain the seller's fingerprint, all of which are state requirements". (Bill, 2011)

This paper focuses on a panel of 2,200 US Counties, in 50 States from 1997 to 2010.[19] The final dataset is obtained merging information from several sources.

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[17] Each transaction shows a pawn ticket number, a client's identification number, shop's identification number, transaction date, and classification code for items pawned.

[18] Within the sample of the top 100 pawnshops' clients, 83 individuals had arrest records. "Of these, 58 had accumulated 300 convictions for property as well as other offenses, or an average of 5.2 arrests per individual. Most property crime arrests, 74 per cent, were for theft, 11 per cent for burglary of vehicles, 7 per cent for burglary of homes or businesses, 5 per cent for robbery, and the rest for forgery and car theft. Other infractions mainly involved drug possession (23 per cent) or driving without a license (23 per cent)." A similar analysis, conducted by Comeau and Klofas (2012) for the city of Rochester, NY shows equivalent evidence.

[19] This represents almost 70% of all the US counties. The final sample is obtained merging NACJD county data on reported crimes and Infogroup data on pawnshops. Missing observations on both datasets and the

Data on crime comes from the National Archive of Criminal Justice Data.[20] County-level files are created by NACJD based on agency records in a file obtained from the FBI that also provides aggregated county totals. Eight different types of crimes are reported: larceny, burglary, robbery, motor-vehicle theft, murder, aggravated assault, rape and arson.[21]

Infogroup Academic provided the overall number of pawnshops by county, per year. The data gathering process follows a six-step procedure. In the compilation phase, data is taken directly from sources such as: government, public company filings, utility Information, tourism directories, web compilation and RSS feeds. The second step in the process is the address standardization process followed by a phone verification phase with 40 million calls made per year. The last three phases include a standardization of elements and a duplicate removal, an enhanced content and a final quality check.[22]

Table I reports crime-related summary statistics, expressed by county and normalized per 100,000 people. The average number of pawnshops per county is 5.88, with a standard deviation of 6.32. Larceny is the most common theft crime, followed by burglary and motor vehicles theft.[23] Violent crimes and arson are less

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presence of data-corruption and differences in counties' names and identifiers determines the final size of the dataset.

[20] Data are downloadable at: http://www.icpsr.umich.edu/icpsrweb/content/NACJD/guides/ucr.html#desc_cl. (Accessed date: December 2012)

[21] 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.

[22] More information is available at http://lp.infogroup.com/academic. The sample has an average of 9800 pawnshops per year. These numbers are confirmed by other studies. See - for example - Fellowees and Mabanta (2008), Shackman and Tenney (2006).

[23] 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.

frequent, with the lowest reported crime being murder, with an average of 3.86 and a standard deviation of 5.43.

[TABLE I]

I also add to the analysis a comprehensive set of county time-varying socio-economic controls, obtained from the US Census Bureau[24] and from the Bureau of Labor Statistics-Current Population Survey.[25]

I include income per capita, percentage of people below the poverty line, percentage of unemployment, social security recipients and the average monthly payment per subsidy. Given the type of credit service provided by pawnshops, I add commercial banks and saving institutions per capita. These controls, together with the amount of banking and saving deposits, aim to capture time varying confounding unobservables, related to both the financial penetration in the county and the relative presence of crime. I also include population density and the racial/ethnic composition in the county, which implicitly controls for the presence of possible confounding migration patterns.[26]

Empirical Analysis

I begin by estimating the following OLS equation:

$$y_{i,s,t} = \alpha_i + \gamma_t + \mu_s * \text{year} + X'_{i,s,t}\beta_0 + \#pawnshops_{i,s,t}\beta_1 + \epsilon_{i,s,t} \qquad (1)$$

where *i* indicates the county, *s* the state and *t* the year. The outcome of interest is the number of reported crimes. The analysis focuses on β_1, the relationship

[24] I use http://censtats.census.gov/usa/usa.shtml. (Accessed date: December 2012)
[25] Descriptive statistics of all the controls included in the analysis are shown in Table A1 of the Appendix.
[26] The racial origin is defined according to four categories: White, Black, Asian and Indian American. Moreover each race is divided into Hispanic or Not Hispanic ethnic origin.

between pawnshops and crime.[27] Both measures are expressed in per capita terms. Standard errors are clustered at the county level.

The inclusion of county fixed effects α_i controls for time-invariant unobserved characteristics related to the changes in both pawnshops and crime. Year fixed effects γ_t, state linear trends $\mu_s * year$ and a vector of county time-varying socioeconomic controls $X'_{i,s,t}$, are also included.

Results

Tables II A and II B show the estimates of β_1 for the pooled measure of theft-related crimes (obtained by summing up larceny, burglary, robbery and motor-vehicle theft) and for non-theft crimes (murder, aggravated assault, rape, arson). Column 1 shows the baseline specification with year fixed effects and state linear trends included. In column 2 I add county fixed effects, while in column 3 I include all county time-varying observables.

[TABLE II A – II B]

The inclusion of county fixed effects reduces the magnitude of the pawnshops coefficients both for theft-related crimes (Column 2, Table II A) and for non-theft crimes (Column 2, Table II B). This indicates the presence of positive selection of pawnshops in counties with high levels of crime.

The within county estimate for theft-related crimes is 6.47 significant at the 1% level. Moreover, the inclusion of all county time-varying observables barely affects this estimate: the coefficient is 6.1 significant at the 1%. To put results into perspective, this indicates that an increase of one pawnshop in a county is

[27] The coefficient β_1 is identified using within county variation in pawnshops per capita. 40% of the observations display a change in the number of pawnshops from t-1, with this variation being distributed across 70% of the counties in the sample.

associated with an increase of more than 6 theft-related crimes in the same county.[28] Conversely, Table II B shows no significant effects of pawnshops on non-theft crimes, once county fixed effects are included in the analysis.

Table III A and III B presents the breakdown by type of crime for theft and non-theft crimes, respectively.

[TABLE III A – III B]

All fixed effects and all county observables are included in each regression. I detect a positive and significant effect only for larcenies and burglaries. The coefficient of pawnshops on larcenies is 4.6, significant at the 1% level. The coefficient on burglaries is 1.5 and it is significant at the 5% level. No effect is detected on robberies, motor-vehicle thefts or other non-theft related crimes.

Selection on Unobservables

Given the lack of random assignment, I cannot exclude the possibility that the omission of some time-variant unobservables might be driving the results on larcenies and burglaries.

A possible way to quantify the extent of this concern is to use the Altonji et al. (2005) method of assessing selection on unobservables using selection on observables. The intuition behind the test is to measure how strong the selection on unobservables must be relative to the selection on observables in order to explain away the effects. This strategy relies on a comparison between a regression run with potentially confounding factors controlled for, and one

[28] A one standard deviation increase in the number of pawnshops in a county is associated with a 0.05 standard deviation increase in the number of theft crimes in the same county.

without.[29] A rule of thumb is that any ratio above 1 is acceptable, as it indicates that selection on unobservables must be larger than selection on observables in order to invalidate the results (Nunn and Wantchekon, 2012). In my specification, the Altonjii ratio exceeds 20 for the measure of pooled theft-related crimes.

Robustness Checks

Table IV presents robustness checks for larceny (Row 1) and burglary (Row 2).

[TABLE IV]

Column 1 reports the coefficient when I cluster standard errors at the state level, column 2 shows the results with two-way double clustering at county-year level, taking into account both autocorrelation of the error structure within county over time and the spatial correlation in each year across counties. In column 3 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.[30] Finally, I perform two tests to check the sensitivity to outliers. Column 4 reveals estimates for the sample that drops counties in the top 1% of the pawnshops per capita distribution. Column 5 presents estimates for the sample that does not include the counties in the top 1% of the population distribution.[31, 32] The stability of the coefficient is shown across all different specifications.

[29] Let *c* denote the estimate with controls, and *nc* denote the estimate without controls. The Altonji ratio is computed as $|\frac{\beta_c}{\beta_c-\beta_{nc}}|$.

[30] The Coverage Indicator variable represents the proportion of county data that is not imputed for a given year. The 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. I exclude observations for which the coverage indicator equals 0.

[31] I also eliminate from the sample the top 10%, 20% and 30% of the most populous counties to check whether the result is driven by big cities. Results are stable across all specifications and are omitted only for brevity considerations.

Heterogeneity in the Results

It is plausible that the transaction costs associated with using pawnshops could vary by population density. The anonymity of a big city might in fact amplify the likelihood of pawnshops being a convenient destination for stolen goods. In rural and less densely populated areas, pawnshops might be far from the crime scene. Moreover, in these areas criminal activity is generally less frequent, and residents are more willing to defend the interests of the members of their communities. Such considerations could undermine burglars' incentives to try to use a local pawnshop to sell stolen goods and, hence, to commit a burglary in its proximity.

I investigate for the possible presence of heterogeneous effects performing a sub group analysis, splitting the sample into "low" and "high" population density counties. The two categories are computed with respect to the median density in the sample.

[TABLE V]

Table V shows results in line with the hypothesis that population density can amplify the effects of pawnshops on crime. For the case of larceny, the coefficient is 10.97 and is significant at the 1% level in high densely populated counties, while it is 3.32 significant at the 10% in low-density counties. I detect a similar pattern in the case of burglaries (columns 3 and 4)

Geographical Spillovers

My initial empirical analysis focused on understanding the effects of within-county changes in pawnshops per capita on the changes of theft crimes *in the*

[32] Table A2 shows the results for larcenies and burglaries of a more demanding estimation strategy including county-linear trends. The coefficient for larceny is 2.3, still significant at the 10% level. For the case of burglaries, the coefficient is 0.8 with a p-value of 16%.

same county. I now extend the analysis in order to detect the possible presence of geographical spillover effects of pawnshops on criminal activity.

I construct a measure of pawnshops per capita at the state level, excluding from this measure the concentration of pawnshops in county *i,* (the county where crime is measured). Table VI shows the results of this specification.

[TABLE VI]

The inclusion of the state-level variable does not affect the earlier estimates related to pawnshops per capita in a county (first row of Table VI). Moreover, I find a large and significant coefficient of pawnshops the state level on larceny (22.5 significant at the 10 % level), and on burglaries (14.01 significant at the 1% level).[33]

IV. Responses to Gold Prices

In this section I further address the endogeneity of pawnshops to crime exploiting the exogenous rise in gold prices as a quasi-natural experiment. Before presenting the results I first describe the various mechanisms behind the salience of gold. Then, I define the identification strategy and show the results.

Demand side

Gold-related goods have always been the primary determinant of pawnbrokers' profits. Bos et al. (2012) show that in the US 34% of male and 63% of female

[33] Previous research involving interviews with burglars suggests that the presence of stolen goods markets might affect their choice of whether and where to commit a theft. Knowing that the probability of being caught increases while stolen property is still in their possession, burglars seem to prefer to commit a theft at a maximum distance of half an hour by car from the envisaged resale point. Nevertheless, burglars might take the risk of traveling far from the crime scene, plausibly to avoid suspicions about the origin of the item or to outdistance the good from the place where it was stolen (Sutton, 2010).

clients used jewelry as part of the pledge in pawn transactions, with gold representing roughly 80 percent of the value of all pledges.

Table VII, from Carter and Skiba (2012), reports the number of loans for each collateral category, the percentage of observations, and the average amount and standard deviation of the items pawned for each category. The sample of observations originates from a pawnshop lender in Texas between 1997 and 2002 but can be interpreted as representative of the transactions profile of a typical pawnshop.[34]

[TABLE VII]

Fifty percent of pawnshop loans are collateralized with jewelry, with over half of jewelry consisting of rings, including both men's and women's class and wedding rings. The next most popular category of pledges is televisions and electronics, including satellite dishes, stereos, and CD players. Individuals also commonly pawn tools, household items such as small appliances, sporting equipment, guns, musical instruments, and camera equipment. The average loan amount for loans collateralized by jewels is $96, a value only lower than guns and musical instruments.

What makes jewelry and, in particular, gold so important for pawnbrokers? Besides the fact that gold is a precious metal, the bulk of pawnbrokers' profits originate from melting down the gold received by their clients through the "refinement" process. A refiner takes the rings, necklaces, bracelets and other items and melts them. Professional outfits remove impurities from the metals until they get something close to pure gold.[35] Hence, stolen items, easily transformed

[34] Similar evidence is in fact found in Comeau et al. (2011). See also Fellowees and Mabanta (2008), Shackman and Tenney (2006).

[35] Refiners typically have minimum quantities of metals that they accept and work with. They normally work with several pounds of material, so direct link between clients and refiners can rarely happen.

into an unrecognizable bar of precious metal, can disappear forever from the second-hand market (Sutton, 2010), ending up in the bullion market or in similar places.[36] This process ensures to pawnbrokers a fast and secure way to make profits by dealing with gold-related products.

Supply Side

Even if most thieves have an ever-changing hierarchy of items that they prefer to steal (Sutton, 2010), crime statistics and victim surveys describe how the most commonly stolen items during *burglaries* are cash, jewelry and consumer electrical equipment.[37] Table A3 in the Appendix shows illustrative evidence of the percentage of stolen items specifically during burglaries.[38]

Larcenies are instead a less gold-intensive crime category. Common types of larcenies include shoplifting, pocket picking, purse snatching, and theft of objects from motor vehicles or bicycles: thefts usually not involving jewelry. In 2010, only 11.3% of common larcenies targeted normal buildings, while 35% were from motor vehicles, 17% from shoplifting, 3% bicycles, and 31.8% all others.[39]

Research Design and Identification Strategy

The hypothesis explored in this paper is that shifts in the resale value of gold, while potentially increasing burglars' expected value of committing a theft

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Information can be found online, see: http://www.pawnnerd.com/where-do-pawn-shops-sell-their-gold-and-silver/ or http://www.economist.com/news/finance-and-economics/21591230-falling-price-gold-hurting-pawnbroking-business-hock-and-sinker.

[36] The bullion Market is a forum through which buyers and sellers trade pure gold and silver. The bullion market is open 24 hours a day and is primarily an over-the-counter market. The bullion market has a high turnover rate and most transactions are conducted electronically or by phone. Gold and silver derive their value from their industrial and commercial uses; they can also act as a hedge against inflation.

[37] Similar evidence is found in Fitzgerald and Poynton (2010), Sorensen (2011) and Walters et al. (2013).

[38] Police recorded crime data are from the Sanwdwell Metropolitan Borough Council area of the West Midlands (Burrel and Wellsmith, 2010).

[39] For more info: http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/property-crime/larcenytheftmain .

uniformly in all counties, might cause relatively more thefts in counties with an higher predetermined concentration of markets potentially interested in buying gold products, namely pawnshops.

These premises are the basis of the following OLS estimating equation:

$$y_{i,s,t} = \alpha_i + \gamma_t + X'_{i,s,t}\beta_0 + \left[\#pawn_{i,t=1997} * gold\_prices_t\right]\beta_2 + \epsilon_{i,s,t} \qquad (2)$$

where i indicates the county, s the state and t the year. The coefficient of interest is β_2, the effect on crime of the interaction between the initial concentrations of pawnshops per capita in a county, fixed to the first year of the sample (1997), and the gold price at time t. The geographical distribution of pawnshops, that resembles the differential in gold treatment-intensity across counties, is shown in Figure I.

In this specification, a key role is played by the inclusion of year fixed effects, that partial out from the estimate the direct and uniform effect that the rise of gold prices might have on the growth of theft crimes in *all* counties.[40] I also include county fixed effects and all the county observables included in the previous analysis.

[FIGURE I]

Gold Prices

My study analyzes a period of 14 years, from 1997 to 2010. In the first 9 years of the sample, from 1997 to 2005, gold prices fluctuated significantly rising in

[40] The same reasoning applies to the plausible increase in burglaries reported to police due to a homogenous increase in the value of stolen jewelry.

value by about 37%. From 2006 to 2010 instead, gold prices displayed an impressive increase of almost 200%.[41]

[FIGURE II]

The 2006 spike in gold prices might have led other businesses, such as jewelers and online refineries, to increase or to start their demand for gold, in order to exploit the high-profitability of this new type of commerce. To investigate the presence of heterogeneity in the effects, I split the sample into two periods: 1997-2005 and 2006-2010.

Results

Table VIII reports the results of the estimating equations (2) for burglaries.

[TABLE VIII]

In the baseline specifications I detect a coefficient of 1.00 significant at the 10% level in the first part of the sample (column1) and a coefficient of 0.431 significant at the 1% level in the second part of the sample (column 3). To put these results into perspective, a one standard deviation increase in the initial concentration of pawnshops in a county generates a 0.05 to 0.10 standard deviation increase in the effect of gold prices on burglaries.[42]

In column 2 and 4 I also include in the specification each county observable, fixed at year 1997, interacted with gold prices. Specifically, I include gold prices interacted with: income per capita, percentage of people below the poverty line,

[41] I use as unit of measurement the price of gold in US dollars (averaged over the entire year) per troy ounce. Data are freely downloadable from the following website: http://www.gold.org. (Accessed date: December 2012)

[42] No effect is detected for larcenies as for any other crime. Results are qualitatively similar and robust in both part of the sample if I use the interaction between pawnshops per capita in 1997 and the log of gold prices. Results are omitted only for brevity considerations.

percentage of unemployment, social security recipients, average monthly payment, commercial banks and saving institutions, amount of banking and saving deposits, population density and the racial/ethnic composition in the county (percentages of White, Black, Asian and American Indian population both Hispanic or not Hispanic).

This specification attempts to control for the presence of other possible confounding channels through which the rise of gold prices might have affected the proliferation of burglaries, with different trends in different counties. It is reassuring to notice that the inclusion of these controls strengthen the significance and the magnitude of the effects on burglaries in the first part of the sample, (1.17 significant at the 5%), while it reduces the coefficient of the period 2005-2010 to 0.3, nevertheless still significant at the 10% level. [43, 44]

[43] Further Robustness checks are shown in table A4 and A5 of the Appendix. In column1 I cluster standard errors at the state level, while in column 2 I use two-way clustering at the county/year level. In column 3 I weight the regression using as weight the FBI coverage indicator. In column 4 I eliminate from the sample the counties in the top 1% of the pawnshops' per capita distribution. In column 5 I eliminate from the sample the counties in the top 1% of the population distribution. In column 6 I add state linear trends. Results are robust across all specifications in the first part of the sample (1997-2005) while are more sensitive, especially to the inclusion of state linear trends, from 2006 to 2010. Possible econometric and economic explanations are discussed in footnote 44. Results in the first part of the sample are also robust to the exclusion from the analysis of the year 1997, hence eliminating the presence of possible reverse causality between burglaries and pawnshops in 1997. Results are omitted for brevity considerations only.

[44] Two possible econometric reasons that might explain the extra-sensitivity of the coefficient in the second part of the sample, (with respect to the more stable estimates from 1997 to 2005), are: 1) the use of only 5 years of data (2006-2010); 2) the stable upward trend in gold prices after 2005 that is collinear with the inclusion of state-linear trends. From an economic perspective instead, the decrease in the size of the coefficient is consistent with the possibility that other type of businesses could have entered the resale market for gold, (due to the increase in the potential profitability of this activity). In this case, the measure of pawnshops, if interpreted as a biased measure of the "true size" of the market for stolen goods, could suffer from a time-variant measurement error that could lead to a more severe attenuation bias in the second part of the sample. Other possible explanations are related to the mechanic decrease overtime of the "available gold to steal" in areas with a high concentration of pawnshops or to the progressive understanding by the local community of the involvement of these businesses in the trade of stolen jewelry.

Copper Thefts and the "Red Gold" Rush

The concluding analysis performs an additional falsification test, exploiting the fact that typically pawnshops do not trade copper, as shown in Table VII, even if criminals heavily target objects made with this metal.

The demand for copper from developing nations has generated an intense international copper trade. According to the FBI, copper thieves exploit this demand and the related spike in international prices by stealing and selling the metal to recyclers across the United States.[45] Thieves target electrical sub-stations, cellular towers, telephone landlines, railroads, water wells, construction sites, and vacant homes for lucrative profits.

Table IX displays the estimates of the interaction between copper prices and the initial concentration of pawnshops in the county.[46] In the baseline regression (columns 1 and 3) I include the interaction between pawnshops in 1997 and copper prices while, in columns 2 and 4, I add to the baseline specification the interaction between pawnshops in 1997 and gold prices.

[TABLE IX]

In the first part of the sample (1997-2005) I detect a positive but imprecisely estimated effect of copper prices through the pawnshops channel. Nevertheless, this effect vanishes when I include the interaction between gold prices and pawnshops (column 2). It is reassuring to observe that, despite the presence of high collinearity between the two-interaction terms, (due to a 0.84 correlation between gold and copper prices), pawnshops seem to affect burglaries uniquely through the gold channel. Moreover, from 2006 to 2010 the copper-interaction

[45] See: http://www.fbi.gov/news/stories/2008/december/copper_120308

[46] Data on historical copper price is obtained from the U.S. geological survey at: http://www.usgs.gov/ (Accessed date: December 2012)

term is negative and significant at the 1% level in both specifications, while the gold-interaction term is 0.34, significant at the 5% level.

While I do not want to overemphasize the negative impact that the initial concentration of pawnshops has on burglaries through copper prices, I consider the substitutability across markets for stolen goods, due to oscillation in world prices, an extremely interesting venue for future research.

V. Concluding Remarks

This paper offers one of the first systematic empirical investigations of the effect of stolen goods markets on criminal behavior. Motivated by the richness of anecdotal evidence, I look at this issue through the lens of pawnshops, a business that has long being suspected of being involved in illicit trade. I address the endogeneity of pawnshops to crime in multiple ways.

I first exploit the panel properties of the dataset constructed for the analysis. Results confirm that the concentration of pawnshops in a county is a strong and significant predictor of larcenies and burglaries. The findings are robust to extensive robustness and falsification checks. I also detect the presence of geographical spillover effects on crime and heterogeneity of the effects related to the population density.

I then exploit an exogenous shift in crimes' expected benefits using the rise in gold prices as a quasi-natural experiment, where the intensity of the treatment is given by the initial concentration of pawnshops in the county. Results still confirm the hypothesis that pawnshops strengthen the expected benefits deriving from illegal activity, amplifying the effect that the rise in gold prices has on the proliferation of burglaries.

This paper suggests new directions for future research. A direct spin off of this work would be the analysis of other markets for stolen goods, such as flea

markets, junkyards or online web sites such as EBay or Craigslist. Moreover, entering the "black box" of the mechanism that links demand and supply of crime is critical for the understanding of criminal behavior. Two mechanisms might in fact play an important role in this context. On the one hand, the increase in the size of stolen goods' markets might increase crime by reducing the criminal expected probability of being arrested (negative deterrence effect). On the other hand, the increase in the level of competition in the resale market might push up prices, raising the expected resale value of the stolen item (price effect). Disentangling these two channels might help to shape specific policy interventions that seek to reduce the impact that the proliferation of stolen goods markets can have on criminal behavior.

TABLE I - DESCRIPTIVE STATISTICS (PAWNSHOPS AND CRIMES)

	(1) Observations	(2) Mean	(3) Standard Deviation
Pawnshops	28,430	5.88	6.32
Larcenies	28,430	1,840	1,046
Burglaries	28,430	654.2	394.7
Robberies	28,430	52.74	73.96
Motor/Vehicle Thefts	28,430	190.4	180.0
Murders	28,430	3.86	5.43
Rapes	28,430	27.28	22.44
Assaults	28,430	237.2	203.2
Arsons	28,430	18.13	20.81

Notes: Variables standardized per 100.000 people, by county. Source NACJD, 1997-2010.

TABLE II A – POOLED MEASURE OF THEFT-RELATED CRIMES

	(1) *Baseline*	*(2)* *+ County FE*	*(3)* *+ County Time-Varying Observables*
Pawnshops per Capita	*26.85**** *(6.776)*	*6.475**** *(2.134)*	*6.124**** *(2.177)*
Observations	*28,430*	*28,430*	*27,466*
Adjusted R-squared	*0.160*	*0.850*	*0.855*
YEAR FE	*YES*	*YES*	*YES*
STATE TRENDS	*YES*	*YES*	*YES*
COUNTY FE	*NO*	*YES*	*YES*
County Observables	*NO*	*NO*	*YES*

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Pawnshops and reported crimes are in per capita terms. The pooled measure of theft-related crimes is constructed as the sum of larcenies, robberies, burglaries and motor–vehicle thefts. County observables include percentages of Whites Hispanics, Whites not Hispanics, Blacks Hispanics, Blacks not Hispanics, Asians Hispanics, Asians not Hispanics, American Indians Hispanics, American Indians not Hispanics, 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 capita, amount of banking and saving deposits, population density. Column 1 shows the baseline specification with year FE and state linear trends. In column 2 I add county FE, in column 3 I include all county observables.

TABLE II B – POOLED MEASURE OF NON-THEFT CRIMES

	(1) Baseline	*(2) + County FE*	*(3) + County Time-Varying Observables*
Pawnshops per Capita	*2.440****	*0.00386*	*0.0629*
	(0.626)	*(0.493)*	*(0.498)*
Observations	*28,430*	*28,430*	*27,466*
Adjusted R-squared	*0.310*	*0.724*	*0.737*
YEAR FE	*YES*	*YES*	*YES*
STATE TRENDS	*YES*	*YES*	*YES*
COUNTY FE	*NO*	*YES*	*YES*
County Observables	*NO*	*NO*	*YES*
Potential Confounding Controls	*NO*	*NO*	*NO*

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Pawnshops and reported crimes are in per capita terms. The pooled measure of other crimes is constructed as the sum of murders, rapes, aggravated assaults and arsons. County observables include percentages of Whites Hispanics, Whites not Hispanics, Blacks Hispanics, Blacks not Hispanics, Asians Hispanics, Asians not Hispanics, American Indians Hispanics, American Indians not Hispanics, 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 capita, amount of banking and saving deposits, population density. Column 1 shows the baseline specification with year FE and state linear trends. In column 2 I add county FE, in column 3 I include all county observables.

TABLE III A - THEFT-CRIMES: BREAKDOWN BY TYPE OF CRIME

	(1) Larcenies	*(2) Burglaries*	*(3) Robberies*	*(4) Motor-Vehicle*
Pawnshops per Capita	*4.601****	*1.507***	*-0.0212*	*0.0377*
	(1.683)	*(0.655)*	*(0.0580)*	*(0.173)*
Observations	*27,466*	*27,466*	*27,466*	*27,466*
Adjusted R-squared	*0.841*	*0.795*	*0.916*	*0.845*
Year FE	*YES*	*YES*	*YES*	*YES*
State Trends	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Pawnshops and reported crimes are in per capita terms. The table shows the results from 4 different regressions, one for each type of reported theft-crime: larceny, burglary, robbery and motor vehicle theft. All the specifications include county FE, year FE, state trends and county observables. County observables include percentages of: Whites Hispanics, Whites not Hispanics, Blacks Hispanics, Blacks not Hispanics, Asians Hispanics, Asians not Hispanics, American Indians Hispanics, American Indians not Hispanics, income per capita, percentage of people below the poverty line, unemployment, social security recipients, the average monthly payment per subsidy, commercial banks and saving institutions per capita, the amount of banking and saving deposits and population density.

TABLE III B – NON-THEFT CRIMES: BREAKDOWN BY TYPE OF CRIME

	(1) Murders	*(2) Rapes*	*(3) Assaults*	*(4) Arsons*
Pawnshops per Capita	*0.0165*	*0.0236*	*-0.0322*	*0.0550*
	(0.0196)	*(0.0525)*	*(0.473)*	*(0.0427)*
Observations	*27,466*	*27,466*	*27,466*	*27,466*
Adjusted R-squared	*0.285*	*0.541*	*0.727*	*0.510*
Year FE	*YES*	*YES*	*YES*	*YES*
State Trends	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Pawnshops and reported crimes are in per capita terms. The table shows the results from 4 different regressions, one for each type of reported NON theft-crime: murder, rape, assault and arson. All the specifications include county FE, year FE, state trends and county observables. County observables include percentages of: Whites Hispanics, Whites not Hispanics, Blacks Hispanics, Blacks not Hispanics, Asians Hispanics, Asians not Hispanics, American Indians Hispanics, American Indians not Hispanics, income per capita, percentage of people below the poverty line, unemployment, social security recipients, the average monthly payment per subsidy, commercial banks and saving institutions per capita, the amount of banking and saving deposits and population density.

TABLE IV - ROBUSTNESS CHECKS: LARCENY & BURGLARY

	(1) State-Level Clustering	*(2) Two-Way Clustering (County-Year)*	*(3) Weighted Regression (FBI Coverage)*	*(4) Trimming Top 1% Pawnshops*	*(5) Trimming Top 1% Population*
(1) Pawnshops per Capita	*4.601***	*4.601****	*4.414****	*4.976****	*4.563****
	(2.153)	*(1.611)*	*(1.569)*	*(1.771)*	*(1.689)*
(2) Pawnshops per Capita	*1.507***	*1.507***	*1.467***	*1.591***	*1.504***
	(0.670)	*(0.741)*	*(0.632)*	*(0.682)*	*(0.655)*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*
State Trends	*YES*	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*	*YES*

Notes: *** p<0.01, ** p<0.05, * p<0.1. This table shows the robustness checks for larceny (row 1) and burglary (row 2). Pawnshops and reported crimes are in per capita terms. Column 1 shows the results when I cluster standard errors at the state level, while in column 2 I cluster at the county/year level. In column 3 I perform a weighted regression using as weight the FBI coverage indicator, a measure of the precision of the information related to reported crimes (see footnote 34 for more information). In column 4 I eliminate from the sample the counties in the top 1% of the pawnshops' per capita distribution. In column 5 I eliminate from the sample the counties in the top 1% of the population distribution.

TABLE V – SUB GROUPS ANALYSIS: POPULATION DENSITY

	(1) Larcenies Low	(2) High	(3) Burglaries Low	(4) High
Pawnshops per Capita	3.321*	10.97***	1.289*	2.906**
	(1.968)	(3.774)	(0.750)	(1.374)
Observations	13,788	13,678	13,788	13,678
Adjusted R-squared	0.800	0.845	0.717	0.849
Year FE	YES	YES	YES	YES
State Trends	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the county level. Pawnshops and reported crimes are in per capita terms. Column 1 and 2 show the results for larcenies, while column 3 and 4 show the results for burglaries. The sample is divided in counties below and above the median population density (Low and High, respectively). Percentiles are computed with respect to the density of the county, averaged for each county in the 14 years of the sample (1997 - 2010). All the specifications include all the fixed effects used in the analysis and all county observables.

TABLE VI – GEOGRAPHICAL SPILLOVER ANALYSIS – PAWNSHOPS IN OTHER COUNTIES WITHIN THE STATE

	(1) Larcenies	(2) Burglaries
Pawnshops in the County	4.561***	1.482**
	(1.687)	(0.656)
Pawnshops in the State	22.59*	14.01***
	(12.11)	(4.352)
Observations	27,464	27,464
Adjusted R-squared	0.841	0.795
Year FE	YES	YES
State Trends	YES	YES
County FE	YES	YES
County Observables	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Pawnshops and reported crimes are in per capita terms. In each regression we include: the number of pawnshops per capita in the county where crime is measured (first row) and the number of pawnshops per capita in all the other counties within the same state. In computing the latter I exclude from the numerator the number of pawnshops in the county where crime is measured and from the denominator the population of the county where crime is measured.

TABLE VII - COLLATERAL BY CATEGORY (CARTER AND SKIBA, 2012)

Category	*Observations*	*Relative %*	*Average Loan*	*Standard Deviation*
Jewelry	*199,288*	*49.98%*	*$96.28*	*105.02*
TVs/Electronics	*126,297*	*31.68%*	*$58.80*	*62.34*
Tools/Equipment	*31,600*	*7.93%*	*$50.18*	*60.67*
Household Items	*10552*	*2.65%*	*$42.92*	*44.7*
Missing	*7,833*	*1.96%*	*$63.75*	*72.54*
Guns	*7,734*	*1.94%*	*$146.97*	*98.75*
Instruments	*7,700*	*1.93%*	*$116.92*	*104.66*
Camera/Equipment	*4,052*	*1.02%*	*$75.85*	*77.87*
Miscellaneous	*3,666*	*0.92%*	*$51.50*	*62.46*

Note: This table reports the number of loans for each collateral category, the percentage of observations, and the average amount and standard deviation of the items pawned for each category. All amounts are in 2002 US dollars. The sample of observations is from a pawnshop lender in Texas between 1997 and 2002, (Carter and Skiba, 2012).

TABLE VIII – BURGLARIES' RESPONSES TO GOLD PRICES

	(1)	*(2)*	*(3)*	*(4)*
	1997-2005		*2006-2010*	
	Baseline	*+Controls*Gold*	*Baseline*	*+Controls*Gold*
*Pawnshops(t=1997)*Gold*	*1.000**	*1.173***	*0.431****	*0.306**
	(0.525)	*(0.572)*	*(0.151)*	*(0.161)*
Observations	*17,195*	*17,195*	*10,271*	*10,271*
Adjusted R-squared	*0.809*	*0.81*	*0.863*	*0.865*
Year FE	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*
*Controls*Gold Prices*	*NO*	*YES*	*NO*	*YES*

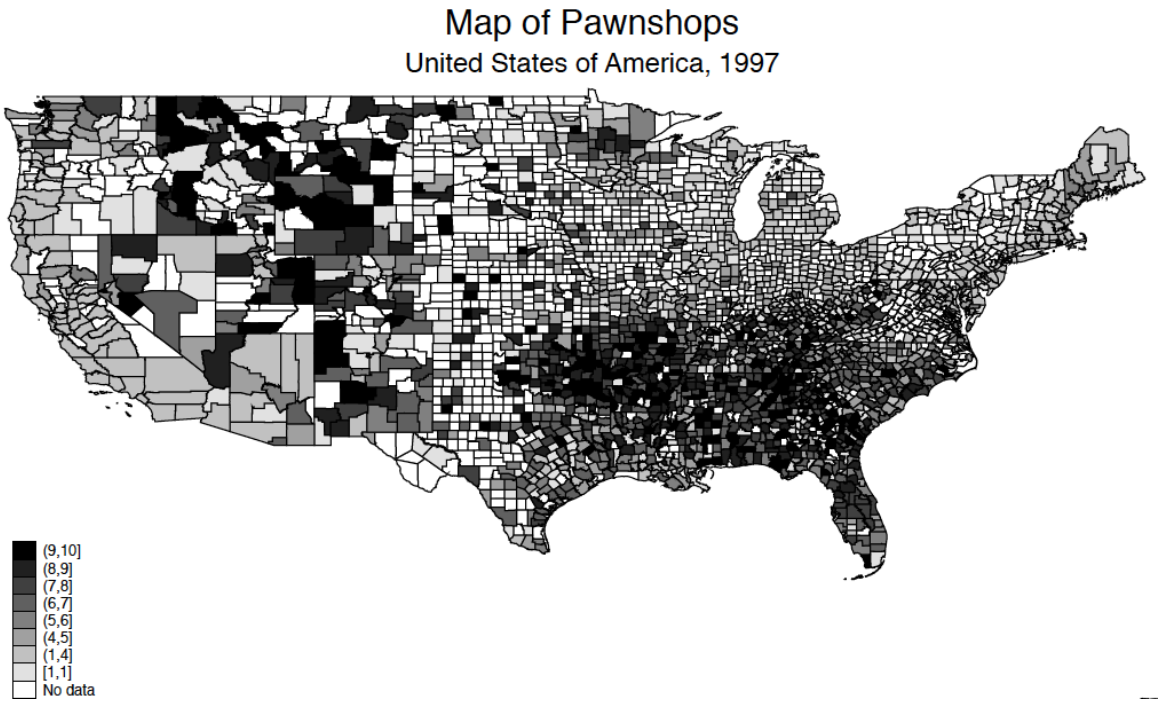
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Pawnshops and reported crimes are in per capita terms. This table shows the results for the interaction between pawnshops per capita in a county, fixed to the first year of the sample (1997), and gold prices. I split the sample in two periods: 1997-2005 (columns 1 and 2) and 2006-2010 (columns 3 and 4). Year FE, county FE and all county observables are included in all specifications. In columns 2 and 4 I add the interaction between all county observables fixed at the first year of the sample and gold prices. I include the interaction of gold prices with: percentages of Whites Hispanics, Whites not Hispanics, Blacks Hispanics, Blacks not Hispanics, Asians Hispanics, Asians not Hispanics, American Indians Hispanics, American Indians not Hispanics, 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 capita, amount of banking and saving deposits, population density.

TABLE IX - FALSIFICATION TESTS: COPPER PRICES

	(1) *1997-2005* *Baseline*	*(2)* *+ Pawnshops * Gold*	*(3)* *2006-2010* *Baseline*	*(4)* *+Pawnshops * Gold*
*Pawnshops (t=1997)**Gold***		*1.267*		*0.344***
		(0.936)		*(0.147)*
*Pawnshops (t=1997)**Copper***	*0.802*	*-0.334*	*-2.004****	*-1.820****
	(0.516)	*(0.912)*	*(0.437)*	*(0.418)*
Observations	*17,195*	*17,195*	*10,271*	*10,271*
Adjusted R-squared	*0.809*	*0.809*	*0.863*	*0.864*
County FE	*YES*	*YES*	*YES*	*YES*
Year FE	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*

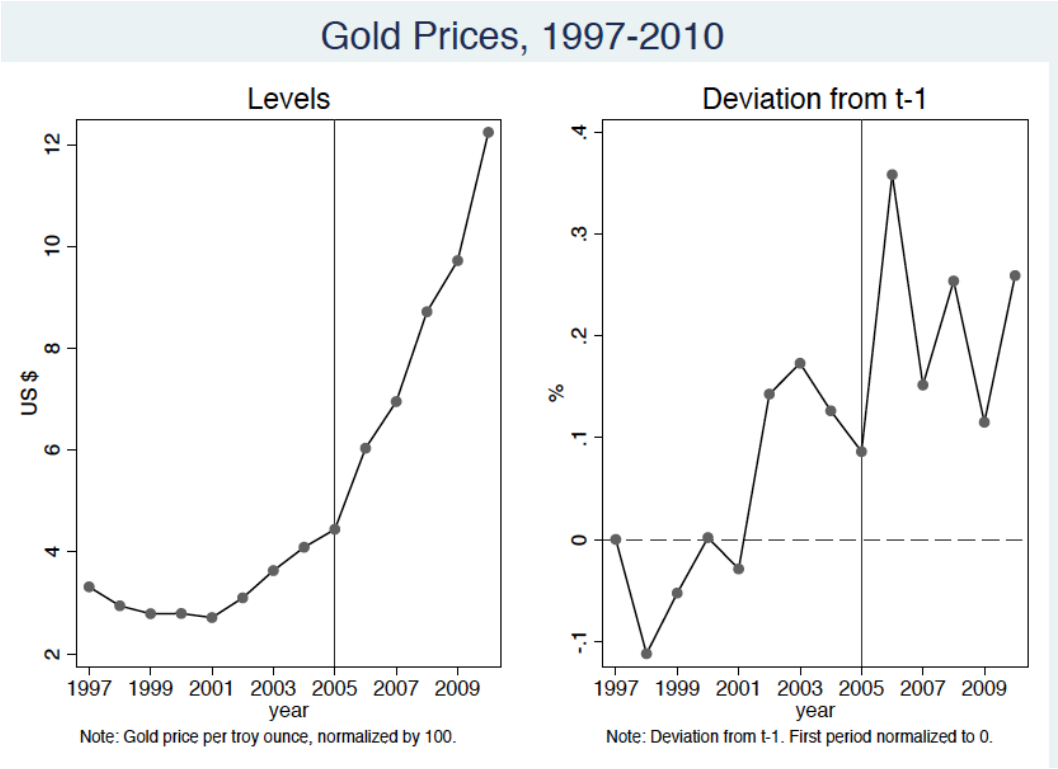
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. Burglary is the dependent variable. In column 1 and 2 I show the results for the first part of the sample (1997-2005) while in column 3 and 4 I show the results for the second part of the sample (2006-2010). In the baseline specification I estimate the interaction between copper prices and pawnshops per capita in the county, fixed in 1997. In Columns 2 and 4 I add to the baseline specification the interaction between gold prices and pawnshops per capita in the county, fixed at 1997.

Figure 1: Pawnshops in the United States



Notes: Figure 1 shows the geographical distribution of pawnshops in the United States for the year 1997. In this figure, I show the pawnshops distribution by deciles computed using the normalized measure of pawnshops per 100,000 inhabitants. Alaska and Hawaii are eliminated from the map for illustrative purposes only.

Figure 2: Gold Prices 1997 - 2010



Notes: Figure II shows the evolution of gold prices, from 1997 to 2010. I use as unit of measurement the normalized price of gold in US dollars, averaged over the entire year per troy ounce. The left-hand side figure shows the gold prices dynamic in levels, while the right-hand figure shows the gold prices evolution expressed as percentage changes from t-1. After 2005, the percentage annual increase is always above 10% with a pick of 37% increase in 2006 with respect to 2005.

VI. Appendix

Crimes Definition:

1. Murder (criminal homicide): The willful (non negligent) killing of one hum an being by another.
2. Forcible rape: The carnal knowledge of a female forcibly and against her will.
3. Robbery: The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.
4. Aggravated assault: An unlawful attack by one person upon another for the purpose of in inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm.
5. Burglary: The unlawful entry of a structure to commit a felony or a theft.
6. Larceny: The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Common types of larcenies include shoplifting, pocket picking, purse snatching, theft of objects from motor vehicles, theft of bicycles and theft of items from buildings in which the offender has legal access.
7. Motor vehicle theft: The theft or attempted theft of a motor vehicle.
8. Arson: any willful or malicious burning or attempting to burn, with or without intent to defraud, a dwelling house, public building, motor vehicle or aircraft, personal property of another, etc.

Hierarchy Rule

In some cases, a single incident may have consisted of two distinct offenses. For example, during the course of a robbery, a victim may have been fatally shot. In cases in which multiple offenses are committed by the same offender against the same victim during a given felonious act, the hierarchy rule is employed to determine how the crime is classified. A crime is classified according to the most serious offense committed. Importantly, the hierarchy rule does not apply to the offense of arson. In fact, when arson is involved in a multiple offense situation, the reporting agency must report two part I offenses, the arson as well as the additional part I offense. The preceding list is ranked according to the hierarchy rule.

TABLE A1- DESCRIPTIVE STATISTICS COUNTY OBSERVABLES

	(1) *Mean*	*(2)* *Standard Deviation*
% White – Not Hispanic	*0.79*	*0.18*
% White – Hispanic	*0.06*	*0.12*
% Black – Hispanic	*0.00*	*0.00*
% Black – Not Hispanic	*0.10*	*0.14*
% Asian – Hispanic	*0.01*	*0.02*
% Asian – Not Hispanic	*0.0*	*0.00*
% American Indian – Hispanic	*0.00*	*0.0*
% American Indian – Not Hispanic	*0.01*	*0.06*
% Unemployment	*6.0*	*2.7*
Income per capita	*27,365*	*7,852*
People below the poverty line	*16,278*	*53,982*
Number of banks and savings institutions	*39.82*	*17.73*
Poverty standardized	*0.146*	*0.06*
Social Security recipients	*20,488*	*47,166*
Density	*318.5*	*2,019*
Social security average monthly payment	*411.2*	*75.6*

Notes: Source US Census Bureau, 1997-2010

TABLE A2 – ROBUSTNESS TO THE INCLUSION OF COUNTY TRENDS

	(1) *Larcenies*	*(2)* *Burglaries*
Pawnshops	*2.341**	*0.801*
	(1.246)	*(0.581)*
Observations	*27,466*	*27,466*
Adjusted R-squared	*0.887*	*0.845*
Year FE	*YES*	*YES*
County Trends	*YES*	*YES*
County FE	*YES*	*YES*
County Observables	*YES*	*YES*

*** p<0.01, ** p<0.05, * p<0.1. All the standard errors are clustered at the county level. This table shows the results for larcenies and burglaries when county-linear trends are included. I also include county fixed effects, year fixed effects and all county observables. Pawnshops and reported crimes are in per capita terms. All the specifications include county FE, year FE, state trends and county observables. County observables include percentages of: Whites Hispanics, Whites not Hispanics, Blacks Hispanics, Blacks not Hispanics, Asians Hispanics, Asians not Hispanics, American Indians Hispanics, American Indians not Hispanics, income per capita, percentage of people below the poverty line, unemployment, social security recipients, the average monthly payment per subsidy, commercial banks and saving institutions per capita, the amount of banking and saving deposits and population density.

Table A3- Items stolen during burglaries - (Burrel and Wellsmith, 2010)

Cash	*40%*	*Documents*	*5%*
Jewelry	***31%***	*Ornaments*	*5%*
Audio	*25%*	*Food*	*5%*
VCR	*17%*	*Tools*	*5%*
TV	*17%*	*Furniture*	*3%*
Personal	*12%*	*Cigarettes*	*3%*
Telecom	*12%*	*Vehicles*	*2%*
Computer	*11%*	*Cycle*	*2%*
Photographic	*11%*	*DVD*	*2%*
Games	*10%*	*Building*	*1%*
Purse	*10%*	*Garden*	*1%*
Cards	*10%*	*Digital*	*0%*
Luggage	*9%*	*Sports*	*0%*
Clothing	*9%*	*Antiques*	*0%*
Domestic	*7%*		
Keys	*6%*		

Notes: This table shows the percentage of the stolen items during burglaries. Police recorded crime data are from the Sanwdwell Metropolitan Borough Council area of the West Midlands. The period covered is from 1997 to 2003. Percentage do not sum to 100 due to the stealing of multiple categories.

TABLE A4 – BURGLARIES' RESPONSE TO GOLD PRICES, ROBUSTNESS 1997-2005

	(1) State level Clustering	*(2) Two-Way Clustering*	*(3) Weighted Regression: FBI Coverage*	*(4) Trimming: Top 1% Pawnshops*	*(5) Trimming: Top 1% Population*	*(6) +State Linear Trends*
*Pawnshops (t=1997)*Gold*	*1.173**	*1.173**	*1.216***	*1.398***	*1.182***	*1.13***
	(0.631)	*(0.701)*	*(0.573)*	*(0.655)*	*(0.573)*	*(0.60)*
Observations	*17,195*	*17,195*	*17,195*	*17,021*	*17,020*	*17,195*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
*Controls*Gold Prices*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Notes: *** p<0.01, ** p<0.05, * p<0.1. This Table shows the robustness checks for the specification where I include the interaction term between pawnshops per capita in 1997 and gold prices. In this table I focus on the first part of the sample, from 1997 to 2005. Column 1 shows the results when I cluster at the state level, while in column 2 I use two-way clustering at the county/year level. In column 3 I perform a weighted regression using as weight the FBI coverage indicator. In column 4 I eliminate from the sample the counties in the top 1% of the pawnshops' per capita distribution. In column 5 I eliminate from the sample the counties in the top 1% of the population distribution. In column 6 I add state linear trends.

TABLE A5 – BURGLARIES' RESPONSE TO GOLD PRICES, ROBUSTNESS 2006-2010

	(1) State level Clustering	*(2) Two-Way Clustering*	*(3) Weighted Regression: FBI Coverage*	*(4) Trimming: Top 1% Pawnshops*	*(5) Trimming: Top 1% Population*	*(6) + State Linear Trends*
*Pawnshops (t=1997)*Gold*	*0.306*	*0.306*	*0.295**	*0.265*	*0.302**	*0.11*
	(0.197)	*(0.198)*	*(0.153)*	*(0.186)*	*(0.162)*	*(0.17)*
Observations	*10,271*	*10,271*	*10,271*	*10,163*	*10,163*	*10,271*
Adjusted R-squared	*0.810*	*-0.060*	*0.816*	*0.810*	*0.809*	*0.809*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County Observables	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
*Controls*Gold Prices*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Notes: *** p<0.01, ** p<0.05, * p<0.1. This Table shows the robustness checks for the specification where I include the interaction term between pawnshops per capita in 1997 and gold prices. In this table I focus on the second part of the sample, from 2006 to 2010. Column 1 shows the results when I cluster at the state level, while in column 2 I use two way clustering at the county/year level. In column 3 I perform a weighted regression using as weight the FBI coverage indicator. In column 4 I eliminate from the sample the counties in the top 1% of the pawnshops' per capita distribution. In column 5 I eliminate from the sample the counties in the top 1% of the population distribution. In column 6 I add state linear trends.

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

By ROCCO D'ESTE *

This chapter investigates the effects of crystal methamphetamines markets on crime. I use as a source of identifying variation Over-the-Counter (OTC) restrictions to meth's critical inputs of production. Heavy crystal-meth addicts typically produce this substance in clandestine "home-labs". Several quasi-experimental designs are performed on a newly assembled panel dataset. This unveils the interlinkages between drugs and criminal activity, combining Drugs Enforcement Agency (DEA) and FBI county-level information. A difference-in differences (DD) design shows that OTC restrictions led to a decline of 5% to 10% in both property and violent crimes. The effects of OTC restrictions are stronger (i.e. more negative) in rural counties where meth production and abuse typically takes place. This chapter contains robustness checks and placebo tests.

I. Introduction

The market for illegal drugs – in its main components of production, distribution and consumption – generates an annual social cost for the United States estimated around $200 billion. This value reflects lost productivity, environmental destruction, healthcare expenditures, and criminal activity (ONDCP, 2007). This paper focuses on the drugs-crime nexus, utterly pervasive in the United States of America. Almost 50% of all US prisoners are in fact clinically addicted to marijuana, crack cocaine, powdered cocaine, heroin, or crystal meth (NACDD, 2014).

It is worth considering that the expansion of illegal drugs markets can exacerbate criminal activity via three major channels: *economic*, related to users' need to support drug-habits or to their inability to work, typically resulting in the proliferation of theft crimes; *pharmacological*, associated with the psychosis arising with immediate or chronic drugs' effects, leading to any form of physical

and sexual violence; and *systemic*, connected with the production and trafficking of the drug itself, exemplified by gangs' violence in the streets to gain control over the territory (Goldstein, 1985).

More indirectly, the relocation of police effort and public resources – aimed at containing the growth of this dangerous market – might generate unintended consequences. These arise if criminals specialize in different illegal activities characterized by lower probability of detection, or if detrimental peer effects in severely overcrowded prisons influence inmates' likelihood of reoffending (FBI, 2010).

Recognizing and quantifying these effects is a key factor to implement cost-effective policies. Well-shaped interventions might in fact target the expansion of these dangerous markets, while reducing the associated level of criminal activity. However, assessing the existence, empirical relevance and direction of causality of these effects has proven difficult.

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

This paper contributes to the literature on the determinants of crime. I focus on crystal methamphetamine, a highly addictive, neurotoxic synthetic substance. Local law-enforcement agencies consider it to be one of the most dangerous illicit drugs in the United States, due to its asserted role in generating thefts, violence and sex offenses. These crimes are typically perpetrated by extreme abusers when *"under the influence"* of this powerful substance (NACO, 2005).

To address endogeneity issues, I use as a source of identifying variation a *shock to domestic production*. This is triggered by the enactment of policy

interventions restricting the access to methamphetamines' critical chemical inputs of production: ephedrine or pseudoephedrine. These chemicals were contained in cold-medicines that – prior to these restrictions – were easy to obtain from pharmacies and local shops. These chemicals were used, together with legal products readily available to the public, to synthesize methamphetamines in clandestine "home-labs".

Extreme methamphetamine abusers typically ran these labs, mainly to sustain their drug habit and those of their close network of acquaintances (DEA, 2010). In practice, policy interventions studied in this paper exogenously reduced crystal-meth exposure to potentially dangerous extreme methamphetamine's users (i.e. *"meth-heads"*).

The effect on crime is *ex-ante* ambiguous. On the one end, these policies could have led to an upsurge of appropriative and violent crimes. These might have been committed by extreme drug-addicts to offset the implicitly higher costs of addiction. On the other end, OTC restrictions could have pushed extreme abusers to decrease the intensive margin of consumption or to quit. This might have reduced crime committed to sustain the habit or "under the influence".

I primarily design the empirical analysis to investigate the effects of these laws. 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 markets for illegal drugs and criminal activity. It combines DEA detailed information on location and number of clandestine meth-labs, prices and purity of methamphetamines and other illegal substances, with FBI data on property and violent crimes, circumstances surrounding homicides, arrests for possession and sale of a variety of drugs. I also use data on hospitalizations from abuse of several typologies of illegal drugs as well as a wide set of socio-economic controls. These are obtained from a variety of sources.

First, I investigate the direct effects of OTC restrictions on criminal activity. I use a reduced-form DD design. I compare differences in crime between counties belonging to: i) states implementing OTC regulations in 2005 and ii) states that did not adopt any OTC restrictions (before and after the implementation of these interventions).

Significant differences in the diffusion of distinct typologies of illegal drugs (such as crystal-meth, heroin, crack or powdered cocaine) provide a rationale to the endogenous implementation of "anti-meth" laws, only in some US states. Nevertheless, the validity of a DD design relies on the critical identifying assumption of conditional parallel trends. I explore the merits of this assumption in a graphical analysis. I show reassuring pre-trends for both property and violent crimes. I also observe a sharp decline in criminal activity post regulation, concentrated in treated states.

The empirical analysis reveals a significant reduction of 5% to 10% in burglaries, larcenies, aggravated assaults and murders. The estimates are robust in the event-study analysis, with the inclusion of i) county FE, ii) a wide range of socio-economic controls, iii) state-specific linear and quadratic trends, the weighting of the regressions by a measure of the quality of the information on reported crimes, different functional forms, and estimation techniques. I also perform placebo tests on Internet and "white-collar" financial crimes. As expected, I do not detect any effects on crimes plausibly unrelated to the proliferation of this neurotoxic substance.

Two distinct triple-differences designs strengthen the findings of this paper. OTC restrictions reduced significantly more criminal activity in treated rural counties. This is where crystal methamphetamines' production and heavy abuse typically takes place (DEA, 2010).

I then devote the central part of the paper (presented in chapter 4 of this thesis) exploring potential mechanisms. First, I include in the analysis DEA data on

clandestine meth-labs seized by law enforcement agencies. I detect a 38% decrease following OTC restrictions, mainly driven by small-medium capacity meth-labs. These estimates – arguably – represent a lower bound of the real reduction in the number of operating labs (Dobkin et. al, 2014). This evidence strengthens the hypothesis that the reduction in crime is strongly associated with the disruption of the domestic market for crystal meth.

Second, I investigate the drugs-violence link. I analyze county-level data encompassing the detailed circumstances under which homicides occurred. The analysis does not reveal any effects on murders associated with police shootouts or gangs related killings. Hence, I do not detect any effect on the *systemic* violence, which is typically connected to the production and/or distribution of "more professional" illegal drugs markets. Conversely, I estimate a significant 8% drop in homicides associated with episodes of violent altercations. These might be more related to the psychotic (medically proven) violent effects arising when users are under the influence of crystal-meth (McKetin et al., 2014).

Third, I examine the presence of unintended consequences of OTC restrictions. The lack of any effect on arrests for sales or possession of marijuana, cocaine and heroine – while serving the purpose of being a well-suited falsification for this analysis – suggests that the market for drugs did not significantly shift towards the trafficking or the demand of other illicit substances. Moreover, a spatial analysis concentrated on control counties sharing the borders with treated states does not reveal any geographical relocation of meth-production or criminal activity.

Therefore, based on: i) the exploration of the underlying mechanisms, ii) additional descriptive evidence from FBI and DEA, iii) ethnographies studying the behavior of heavy meth-addicts, I propose a simple theoretical dynamic-framework. This framework guides and sharpens the interpretation of the findings.

The set-up of the model matches qualitative features of the domestic market of crystal methamphetamines. I focus on the decision process of a typical drug-addict, who needs to commit crime to sustain his habit. I model the introduction of OTC restrictions as an unexpected shock to crystal meth prices: intense users developed their addiction before the policy intervention, when they had "low-cost" access to crystal meth. This is either because they were small producers, or because the substance was manufactured within their close network of acquaintances, sharing the same habit.

The model, while acknowledging the potential ambiguous effect of change in meth-prices on criminal behavior, provides an additional set of testable implications. These are corroborated by the subsequent empirical analysis or by further descriptive/qualitative evidence.

Testable Implication 1 predicts that OTC restrictions should lead to a monotonic reduction in the use of methamphetamines. I investigate this hypothesis using: 1) "Monitoring the Future", an ongoing study of the behaviors, attitudes, and values of American secondary school students, college students, and young adults and 2) Quest Diagnostics, the major providers of illegal drugs testing in the United States.

These two separate sources *descriptively* confirm Testable Implication 1. In both cases, official documentation shows a national a drop in crystal-methamphetamines lifetime prevalence of almost 30% from 2004 to 2005 among 12 graders, and a reduction of 15.2% and 35.7% (in 2005 and 2006, with respect to 2004) for workplace positive tests due to crystal meth. The drop in the abuse of the substance is also confirmed by numerous ethnographies describing the impact of OTC restrictions on the lives of extreme meth addicts (Sexton et al. 2008, Lopez, 2014).

This evidence leads to *Testable Implication 2: OTC restrictions, by decreasing the intensive/extensive margin of consumption of extreme-abusers, should have*

led to an increase in "cold turkey" episodes, meth-hospitalizations due to rehabilitation, detoxification and withdrawal symptoms. I formally test this hypothesis using the Treatment Episode Data Set (TEDS). This database contains drugs-specifics information of the episodes of voluntary public hospitalizations for detoxification, rehabilitation and ambulatory.

The DD analysis reveals an increase of 34% for the case of hospitalizations associated with methamphetamines' addiction, significant at the 5% level. Convincingly, this effect is isolated only to the case of crystal methamphetamines. No effect is detected on hospitalizations due to abuse of alcohol or several other illegal substances such as crack-cocaine, heroin, marijuana and LSD.

Testable Implication 3 predicts the presence of potential heterogeneous and non-monotonic effects of the laws on criminal activity across US states. As a partial confirmation of this prediction, the analysis suggests that some US state experienced an increase in crime after OTC restrictions. Despite the difficulty to provide a more profound rationale to this differential impact, the analysis indicates that the reduction in crime has been stronger (i.e. more negative) in states with higher pre-determined prevalence of methamphetamine users.

Overall, the findings – alongside the evidence gathered from medical, ethnographic and practitioners' sources – support the hypothesis that OTC restrictions put a cap on "meth-epidemic". This seems to have played a major role in slowing-down the spiral of heavy drugs' abuse and associated criminal behavior, soaring "under the influence" of this powerful substance. This work ultimately suggests that embedding the criminogenic effects of illegal drugs' abuse within the cost-benefit analysis developed in Becker (1968), might provide a richer framework through which analyzing criminal behavior's production function.

From a policy perspective, this paper emphasizes the benefits of supply-side interventions leading to a short-term reduction in criminal activity. Nevertheless,

it also highlights the importance of taking into account the demand-side of the market, with a focus on communities where the abuse of the illegal substance is extremely acute.

More broadly, while the exploration of the mechanisms leading to presumed heterogeneous and non-monotonic effects of anti-drugs laws on crime is beyond the scope of this work, this paper suggests two additional aspects worth exploring. First, it is important to carefully consider the psychotic effects specific to each "hard-drug". These could plausibly lead to stronger *criminogenic* effects either when users are *"under the influence"* (e.g. *stimulants* such as crack cocaine, amphetamines and bath salts) or – conversely – when they are *"on withdrawal"* (e.g. *narcotics* such as opium, morphine and heroin). Second, a key role could be played the presence of possible non-linearity in the elasticity of demand. This might generate differential effects on criminal activity within different price-range.[47] In my view, these and other interesting aspects provides fertile ground for the emergence of both new theoretical and empirical research.

This paper unfolds as follows: section II describes the related literature; section III provides the institutional background; section IV presents the data sources and the main empirical design; section V reports related-results, robustness checks and placebo exercises; chapter 4 explores the underlying mechanisms, it also presents the theoretical framework, the set of testable implications and the subsequent empirical analysis. Chapter 5 presents an instrumental variable approach, designed to address the endogenous opening of meth-labs and to detect its direct effects on crime. This chapter also presents an additional DD design exploiting the subsequent CMEA federal act, and the examination of the long-run effects of OTC restrictions.

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[47] Two recent studies on elasticity of demand for illegal drugs are: Olmstead et al. (2015) and Gallet (2014).

II. Related Literature

My findings contribute to several strands of the literature. To the extent of my knowledge, this is the first study that credibly overcomes simultaneity issues typically linking drug's abuse and criminal propensity. I achieve this by exploiting OTC policies restricting the access to crystal meth chemical precursors, performed in clandestine labs. Extreme methamphetamine abusers typically ran these operations, mainly to sustain their drug habit and those of their close network of acquaintances (DEA, 2010). In practice, these changes in policy allow for the exploration of the effects of an exogenous change in illegal drug exposure on criminal activity.[48]

My study is also closely related to a recent literature that focuses on how drugs-policy intervention affects crime. Melissa Dell (2014) 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. This was linked to PAN aggressive policy that weakened incumbent criminals. 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. This led to a significant reduction of all these types of felonies.

This paper complements two other works on methamphetamines market. Dobkin and Nicosia (2009) estimates the effects of a different government effort

[48]One of the first pioneering analyses 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.

aimed at reducing the supply of this substance in California in the year 1995.[49] They show that when 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 substantial reductions in property or violent crime. Dobkin, Nicosia and Weinberg (2014), focus on the OTC regulations that I investigate. They use various rich administrative datasets and mainly focus on methamphetamines' market. Consistent with my results, they detect a 36% decrease in meth-labs seized by police. My study benefits from the richness of their administrative information to get important insights about this market. Importantly, I look at the effects of OTC restrictions from a different angle. In fact, I focus on unveiling the impact of crystal methamphetamines on crime, and identifying the underlying operating channels.[50]

III. Institutional Background

This section provides a comprehensive institutional background on crystal methamphetamines. I first examine the effects of the drug, emphasizing the links between abuse and criminal behavior. Then, I focus on the peculiarities of its domestic market. Finally, I report the details of states and federal legislations limiting the access to meth chemical precursors.

[49] 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).

[50] My study uses county-level annual variation on a sample of 38 US states while Dobkin et al. use state-monthly variation on all US states. See section III and IV for details.

Methamphetamines' 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 to produce a release of high levels of dopamine and neurotransmitters into the brain. This generates sensations of self-confidence, energy, alertness, pleasure, and sexual arousal.

With repeated use, meth exhausts accumulations of dopamine in the brain, simultaneously destroying the wiring of dopamine receptors. 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.[51]

Chronic abuse can lead to psychotic behavior, hallucinations, paranoia, violent rages, mood disturbances, insomnia, psychosis, poor coping abilities, sexual dysfunction, dermatological conditions and "meth mouth", a dental condition characterized by severe decay and loss of teeth, fracture and enamel erosion (NIDA, 2002). The termination of use can result in depression, fatigue, anxiety, agitation, vivid or lucid dreams, suicidal temptation, psychosis resembling schizophrenia and paranoia (ONDCP 2003).[52]

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[51] 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).

[52] Unlike many other illegal drugs, methamphetamine is a drug that appeals equally to men and women. All of the national data sets show an almost equal gender split for self reported meth use. Users also tend to be White and in their 20s and 30s. Though both cocaine and methamphetamine are stimulants, a comparison

Methamphetamines-Related Criminal Activity: Supportive Evidence

Crystal methamphetamine enormously raises the energy level of a meth-addict when under the influence. Conversely, it produces fatigue, excess sleep and suicidal temptations, when he is not. Consequently, while a significant proportion of methamphetamine-related property crimes can be attributed to users' need to fund their drug purchases:

"… *Many property and violent crimes are more likely a result of the pharmacological stimulant effects of this substance, which is at its peak when the extreme meth-user is under the influence* " (DEA, 2013). [53]

McKetin et al. (2014) administered a structured interview on a sample 238 individuals, characterized by a different level of meth consumption and addiction.[54] They highlight a clear dose–response increase in violent behavior. This effect was especially large for frequent methamphetamine use (i.e. 16+ days of use in the past month), which increased the odds of violent behavior 10 fold (threefold with less frequent use). These results indicate that the probability of violent behavior increases from 10% during periods of abstinence to 60% during periods of heavy methamphetamine abuse.[55]

The National Association of Counties (NACO) administers an annual telephone survey to law enforcement agencies. Their scope is to investigate the

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of characteristics of methamphetamine users and cocaine or crack users indicates that the two drugs do not, for the most part, share a common user group; that is, the drugs do not seem to substitute for each other or appeal to the same users (Hunt et. Al, 2006).

[53] To give a simple sense of the power of this illegal drug, while the high from cocaine can last from 30 minutes to one hour the rush from methamphetamine lasts from 8 to 24 hours. More information can be found at: http://www.drugabuse.gov

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

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

impact of various illegal drugs on the proliferation of criminal activity. In 2005, law enforcement officials from 500 counties in 45 US states were asked to select the illegal drug that was the biggest problem in their county. Crystal methamphetamine ranked first in 58% of the counties taking part to the survey, due to its pervasive power in generating thefts, property crimes and any sort of physical and sexual violence.[56]

Arrestee Drug Abuse Monitoring Data (ADAM) provides further insights. In 2003 (the last year when this data were published before the implementation of OTC restrictions) the national mean of the adult male arrestee population for property and violent crimes who tested positive for methamphetamine was 4.7%. The national mean of arrestees who reported the use of methamphetamine within the previous year in 2003 was 7.7%.

These figures hide a great deal of variation across geographical locations. As an example, ADAM program data indicate that 12% of adult male arrestees in Seattle tested positive for methamphetamine in 2003, while 32.1% tested positive in Spokane, 45% in Sacramento, 28% in Portland and 44% in San Diego (ADAM, 2003).[57]

The Domestic Market for Methamphetamines

Imported illegal drugs such as cocaine or heroin have a hierarchical and complex distributional system. These substances originate from agricultural products that need to be harvested, processed at several junctures, shipped, and eventually packaged for different levels of distribution. These steps involve growers, extractors, producers, transporters, smugglers, distributors and numerous

[56] Methamphetamine was followed in the ranking by cocaine (19%), marijuana (17%) and heroin (3%).

[57] More than 51% of the 500 responding local law enforcement agencies reported that up to 20% of arrests made in their counties during the last 5 years were methamphetamine related, while 17% reported that more than 50% were meth-related.

other people that are needed to move the illegal product across borders.

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.

For this reason, the meth "cook" – particularly in the case of smaller labs – is often a heavy meth user who turned into a producer. The "cook" decides to face the risk of a heavier criminal conviction to sustain the drug habit, fostered by the addictive power of the substance.

This process translates into a lack of specialization across different roles in the distributional chains. This generates segmentation across various small illegal meth-markets. 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.[58]

Ephedrine is the essential ingredient in the synthesis of crystal methamphetamine. This chemical is contained in medicines that help relieve the symptoms of a common cold or flu. If not in pure powder, this chemical needs to be separated from the tablets of cold medicine that contain it.[59] For this purpose,

[58] 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. Moreover, meth distribution typically happens 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.

[59] 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

cold tablets are mixed with sodium hydroxide, anhydrous ammonia, iodine, matches containing red phosphorus, Drano (a drain cleaner product), ether, brake and lighter fluid and hydrochloric acid. These are all legal products that can be easily bought in local stores.[60]

The entire chemical process is performed in self-made chemical labs hidden in flats, caravans, garages or hotel rooms. This generally takes about two days and can result in hundreds of thousands of methamphetamine doses. These "Mom and Pop" labs 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 few hours (DEA, 2003).[61]

OTC States and Federal Restrictions

In the last 25 years, the federal government has passed several laws intended to cut the diversion of ephedrine and pseudoephedrine to illegal drug labs.[62] This paper examines the effects of over the counter restrictions, implemented mainly in

[60] The early manufacturers of meth in the U.S. used what is called the P2P method, named after the precursor substance employed, phenyl-2-propanone. This method yields relatively small amounts — less than 10 pounds — of the lower quality dl-methamphetamine and, until regulation of this precursor, was the most common illegal production technique. This was the method associated with motorcycle gang production. Regulation of the precursors used in this method produced a change to the use of other substances, like ephedrine and pseudoephedrine, which result in production of the higher quality d-methamphetamine (Hunt et al., 2007).

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

[62] 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 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).

the year 2005. These policies were implemented as a reaction to a rapid increase in the number of toxic labs where the manufacturing of this substance occurred.

These policies *only* regulated the access to the methamphetamine's precursor chemicals, ephedrine and pseudoephedrine, through: 1) quantity limitations, 2) sales environment restrictions, 3) proof of identification upon purchase 4) logbooks to prevent people from subverting the law by making repeated purchases.[63]

Policy activity restricting the access to methamphetamine's precursor chemicals has not been limited to the state level. Federal legislation took place in 2006 through the Combat Methamphetamine Epidemic Act (CMEA). The last provision of the Federal act became effective September 30, 2006. This set a nationwide baseline standard for how to legally sell these products.[64]

Figure 3 shows a map of the United States highlighting the year in which any OTC restriction (either at the state or federal level) was active for the first time in each state.

[Figure 3]

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

[63] 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.

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

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***, authorizing 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***, where only the federal regulation became effective on September 30 2006. These are: Connecticut, Maryland, Massachusetts, Nevada, New Hampshire, New York, Pennsylvania, Rhode Island.

The timing of the enactment of these laws gave rise to multiple experimental designs. These will be discussed in the rest of the paper and online appendices.

IV. Data Sources and Identification Strategy

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

Data Sources

I assembled an original annual panel dataset, encompassing 2,200 US counties in 50 states from 2001 to 2010, representing 70% of counties with 94% population coverage for all the United States territory.[65]

[65] The final database is obtained merging and constructing county-level information from several sources described in this section. Missing observations on all datasets (FBI, DEA and all databases used US Census Bureau and from the Bureau of Labour Statistics-Current Population) and the presence of data-corruption and differences in counties' names across sources determines the cross-sectional size of the final dataset. Data on

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).[66] 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.[67]

The "Uniform Crime Reporting Program Data: Supplementary Homicide Reports" is accessed through the NAJCD. This provides incident-based information on criminal homicides reported to the police. This database contains information describing the victim, the offender, the weapon used and – when known by investigators – the different circumstances surrounding the homicide.[68]

The National Clandestine Laboratory Register, provided by the US department of Justice, contains dates and addresses of locations where law enforcement agencies reported finding chemicals or other items that indicated the presence of either clandestine drug laboratories or dumpsites.[69] I use this information to

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crime are merged from 2001 (one year after that Methamphetamine Anti-Proliferation Act of 2000 was implemented and the year the state of Utah authorized for the first time) to 2010. Data on meth-labs seizures are public available from 2004. The main empirical analysis focuses from 2001 to 2006 (the year in which CMEA federal act was implemented).

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

[67] 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.

[68] These data are reported at the FBI agency-level. I use crosswalks FBI data – accessed through NAJCD – to match police agencies to US counties. 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). In less than 2% of cases, agencies' territory is included in multiple counties. Due to the impossibility of assigning the homicide category to the correct county, I drop these observations when collapsing agencies measures into county-level measure of different circumstances surrounding the homicide.

[69] These data are public available at: http://www.dea.gov/clan-lab/clan-lab.shtml. (Accessed Date: September 2013). Data on labs and on estimates of price and purity are constructed from the DEA's System

generate a county-level annual-measure of the number of meth-labs seized by the local enforcement agencies. These data are available from 2004.

The empirical analysis uses a wide set of county time-varying socio-economic controls. These are obtained from the US Census Bureau and from the Bureau of Labor Statistics-Current Population.[70] These variables, all summary statistics and other data sources will be discussed when relevant.

Main DD Design: Empirical Strategy Discussion

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

Pre-Existing Differences In Illegal-Drugs Penetration

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

Tables I (A, B and C) summarize means and differences of relevant variables. In these tables, columns (1) and (2) report the mean of each variable for *CMEA Only* and *Early Adopters* states, respectively. Column (3) shows the difference

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).

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

between (1) and (2). I report 10%, 5% and 1% significance levels. Means are computed in the pre-intervention period, from 2001 to 2004, by county or by state. Variables are normalized per 100,000 inhabitants, when meaningful.

[Tables I (A-B-C)]

Table I-A reveals that *CMEA Only* states (states that did not adopt any OTC regulation) were characterized by significantly less methamphetamines production. This information is summarized by a difference in meth-labs seizures of 5.7 per 100,000 inhabitants. Similarly, these states were experiencing significantly fewer hospitalizations due to methamphetamines abuse (-46.4), amphetamines abuse (-23.8) drug-related arrests for sale (-11.1) and possession (-23.8) of other-dangerous non-narcotics. This is the FBI category containing crystal methamphetamines and for sale and possession of synthetic narcotics (-8.1 and 14.2).

In contrast, *CMEA Only* states were characterized by significantly higher arrests for: (i) possession of marijuana (+53), (ii) sale and possession of cocaine, heroin, and derivatives (+25.5 and +33.8). *CMEA only* states also experienced significantly more hospitalizations due to alcohol, cocaine, heroin, and over the counter medicines.

The evidence on the pre-existing differences in criminal activity is more ambiguous (Table I-B). *CMEA Only* states were characterized by fewer larcenies and burglaries (-301.9 and -172.59) but by a higher level of robberies (+35.68). No significant differences are detected for murders or aggravated assaults. Counties belonging to control states experiencing fewer rapes (-2.13) but more episodes of arsons (+4.05).

Table I-C summarizes pre-intervention differences of all socio-economic controls used in the analysis. For brevity considerations, I omit this discussion.

Parallel Trends Assumption

The existence of significant differences in baseline characteristics between *Early Adopters* and *CMEA Only* states – due to the penetration of distinct illegal drugs in different US territory – provides a rationale for the endogenous take up of OTC restrictions from *Early Adopters* states.

The presence of these significant differences does not undermine the validity of the results obtained using a DD estimator, if the assumption of conditional parallel trends in the outcome variable is satisfied.

Figure 4 investigates the reliability of this assumption. I show the evolution in criminal activity – for both treated and control states – from 2001 to 2006. This is the period of analysis in this empirical exercise.

[Figure 4]

Figure 4 reveals a reassuring pattern of criminal activity before states' intervention for larcenies, burglaries, murders and assaults. It also uncovers a sharp reduction in burglaries and larcenies in 2005 and in 2006 and a slight post-regulation reduction in *Early Adopters* states for murders and aggravated assaults.[71] Figure 4 also shows slight increase of violent crimes in *CMEA Only* states, after the enactment of OTC restrictions. This might indicate the presence of geographical relocation across states' borders. This hypothesis will be explicitly tested.

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

V. Results

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

Baseline Results

I use the following DD estimating equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + (Treated * Post)\beta_1 + \varepsilon_{c,s,t} \qquad (1)$$

Here the subscript *c* indicates the county, *s* the state and *t* the year. Outcomes of interest are reported crimes, expressed as $log(1 + x)$. The measure of each crime x is normalized per 100,000 people. The analysis focuses on β_1. This is the coefficient associated with the interaction between *Treated (*an indicator variable taking the value of 1 if the county belongs to an *Early Adopter* state and zero if it belongs to a *CMEA Only* state) and *Post* (an indicator variable taking the value of 1 for years 2005 and 2006, 0 otherwise). Standard errors are clustered at the state level.[72]

The estimating regression (1) includes: 1) county fixed effects α_i, which absorb time-invariant unobserved heterogeneity across counties; 2) year fixed effects γ_t, capturing common shocks and 3) a vector of county time-varying

[72] The sample includes 30 treated states and 8 control states.

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.

[Tables II (A-B)]

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

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

[Table III]

Table III present results for larceny, burglary, assault and murder obtained using equation (1) and including all county time-varying observables. Results are similar in magnitude and precision to the baseline specification. The estimated coefficients are: larceny -8.1%, burglary -7.4% and murder -10%. These coefficients are precisely estimated with a p-value below 5%.[73]

[73] Results for all other crimes are similar in terms of size and magnitude to the ones presented in Table III panel B. Results are omitted for brevity considerations only.

Event-study Analysis

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

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

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

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

[Tables IV (A-B)]

For larceny, I detect a reduction of 10.4% in the year 2005 and of 12.7% in the year 2006. Coefficients are precisely estimated, always below the 1% significance level. Pre-intervention coefficients grow in magnitude (from -0.04 in 2001 to -0.02 in 2004). A significant coefficient is detected only in 2002, hence three years before intervention. For burglary, I detect 8% to 9.8% reduction in the year 2005

and 2006, respectively. Significance levels are below 5%. While pre-intervention coefficients increase overtime (from -0.03 in 2001 to -0.002 in 2004) no significant differential pre-trend is detected. Results for aggravated assault are reported in columns (3). I detect a decrease of 7.7% in 2005, significant at the 10% level. The coefficient in year 2006 is around -4.3%. This is imprecisely estimated. For murder, columns (4), I detect a decrease of 16% in 2005 and 7% in 2006. The coefficient in 2005 has a significance level below 5%, while the coefficient in 2006 is imprecisely estimated.[74] For aggravated assault and murder, no significant pre-intervention pattern is detected. Figure 5 plots the coefficients of the event-study together with 95% confidence intervals reported.

[Figure 5]

For larceny and burglary, this figure shows the presence of a slight pre-intervention increasing trend in treated states, possibly due to the spreading of the meth-epidemic and its role in generating crime. Nevertheless, crucially for the interpretation of the results of this paper, this increase goes in the *opposite* direction of the crime-reducing effect of OTC restrictions.

Table IV-B presents the results obtained through estimating equation (2) for robbery, rape, arson and motor vehicle theft. I do not detect any significant reduction.

Robustness Checks

Tables V (A to E) present the main robustness checks for the event-study analysis. Table V-A shows the results when I add to the baseline specification measures of police officers with arrest powers and civilian employees.

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

These controls, while deepening the extent of the analysis potentially capturing time-varying confounding factors, are not included in the baseline specification. In fact, these can be considered as potential outcomes of policies implemented to eradicate methamphetamines production. Table V-A shows that the magnitude of the coefficients and the significance levels are stable across crimes and are almost identical to the baseline specification.

[Tables V (A-E)]

Table V-B includes states-specific linear trends. This specification increases the magnitude of the estimates for all the category of property and violent crimes (i.e. estimates are more negative).

This result allows for a variety of interpretations. State-specific trends might be an unobserved confounder in the analysis. This is the case if the endogenous decision to adopt OTC restriction is positively correlated linear crime trends. In other words, if factors associated with rising crime increased the pressure for the reform, the inclusion of state-specific time trends, while absorbing this effect, would bias baseline estimates down. From an econometric perspective, 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. Despite the difficulty of disentangling these separate effects, I find encouraging that the inclusion of state-specific trends strengthens the crime-reducing effects of OTC restrictions, rather than weakening it.[75]

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

Table V-C shows the results when I weight the regression by the coverage indicator reported by the agency, a measure of the reliability of the information on crime available to the researcher.[76] Results are stable to this specification.

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

Heterogeneity in the Results: Two Triple DD Designs

Small clandestine production and abuse of crystal meth typically takes place in rural, low populated counties. This partly reflects that meth-producers have to hide the illegal production process. In fact this generates intoxicating fumes and frequent explosions that have to be hidden from the public and from law enforcement officers (DEA, 2006).

[Figure 6]

Figure 6 shows a map of the distribution of labs in the United States in 2004. Categories expressed in deciles, for illustrative purposes only. The production of methamphetamines is spread across the entire county, with higher concentration in central-east states, especially Missouri, Tennessee, Arkansas, Kansas and Indiana.

Figure 7 investigates this relationship, showing the scatterplot and the quadratic fit of the number of methamphetamines' labs seized by law enforcement

[76] 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.

agencies in 2004 in each county, normalized per 100,000 people, and population density in 2001.[77] As expected, it illustrates that a higher concentration of meth-labs seizures is found in low-populated, rural counties.

[Figure 7]

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

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + (T * P)\beta_1 + (D * P)\beta_2 + (T * P * D)\beta_3 + \varepsilon_{c,s,t} \quad (3)$$

Here *T=Treated*, *P=Post* (as in the baseline DD design, equation (1)) and *D=population density* in 2001 (first design) and *meth-labs seized in 2004* (second design).[78] Table VI shows the results for the first design.

[Table VI]

The triple interaction term has a positive coefficient in all specifications. For burglary the coefficient of 0.018 is significant at the 5% level. For aggravated assault the coefficient of 0.015 is significant at the 10%, for murder the coefficient is 0.04 significant at the 1%.

In the second experimental design, I use as a third interaction term the county-level number of meth-labs seizures normalized per 100,000 people (fixed in 2004). This approximates the underlying pre-determined local production of

[77] I use density in 2001 and meth-labs seizures in 2004 because this is the first year when data are available for the two measures, respectively.

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

crystal-meth. The estimating equation is otherwise identical to (3). Table VII shows the results.

[Table VII]

I detect a negative coefficient of the triple interaction term, significant at the 5% level for larceny and assault (-.01 and - .04). For murder, the triple interaction is high in magnitude (-0.048) but not significantly different from 0.

To interpret the results, I note that a one-unit increase in the pre-intervention normalized measure of labs per 100,000 people generates an additional 1.3% decrease in larcenies and 3.8% in aggravated assaults.

Overall, this exercise suggests that the enactment of OTC restriction reduced crime *more* in treated rural counties with a *higher* predetermined concentration of domestic methamphetamines production and – plausibly – of extreme abusers.

Two Placebo Tests: Cyber & Financial Crime

In this section I develop placebo tests on two distinct crime-categories that – reasonably – should not have been affected by the enactment of OTC restrictions. These are cybercrimes and financial "white-collar" crime.

Cybercrimes are fraud-types such as auction fraud, non-delivery, and credit/debit card fraud, as well as non-fraudulent complaints, such as computer intrusions and spam/unsolicited e-mail. State-level measures of cybercrime are obtained from the annual Internet crime report prepared by the National White Collar Crime Center and the FBI.[79] Due to the trans-national nature of this crime, I have analyzed both the state-level measures of complainants and perpetrators per 100,000 people.

[79] These are accessible at http://www.ic3.gov/media/annualreports.aspx

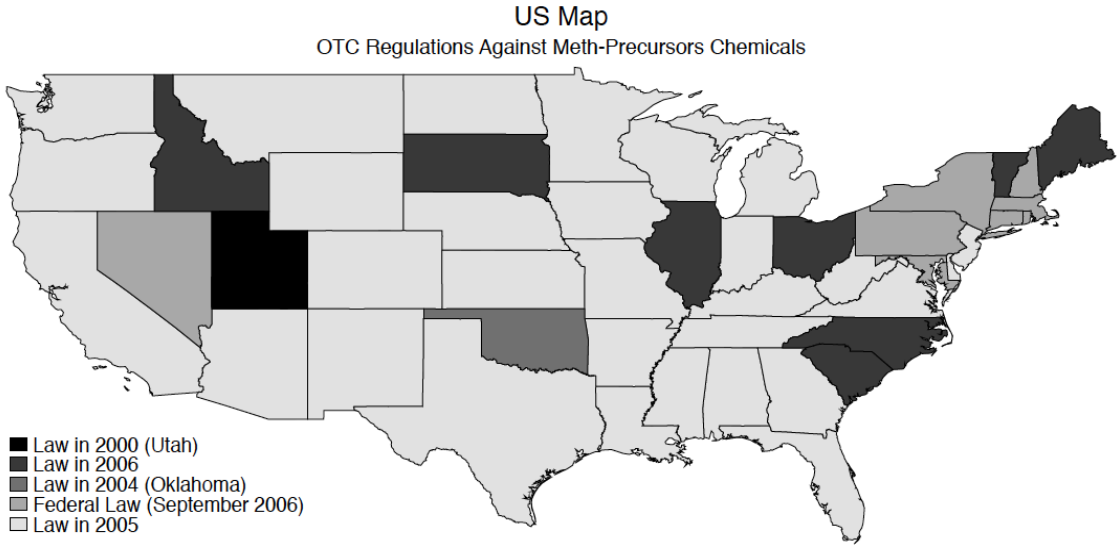
Financial institution fraud and failure investigations (FIF) include mortgage and loan fraud, insider fraud, check fraud, counterfeit negotiable instruments and check kiting. These data are obtained through the FBI web portal.[80] These annual data are at the FBI field office level and are distinct by indictments and convictions.

[Figure 8]

Figure 8 shows the results of estimating equation (2) for both categories of crime. To perform this analysis, I collapsed the mean of socio-economic controls at the state-year level. Due to the placebo nature of the exercise, I plot a more conservative confidence interval of 90%. As expected, no significant effect is detected for cyber and financial crimes.[81]

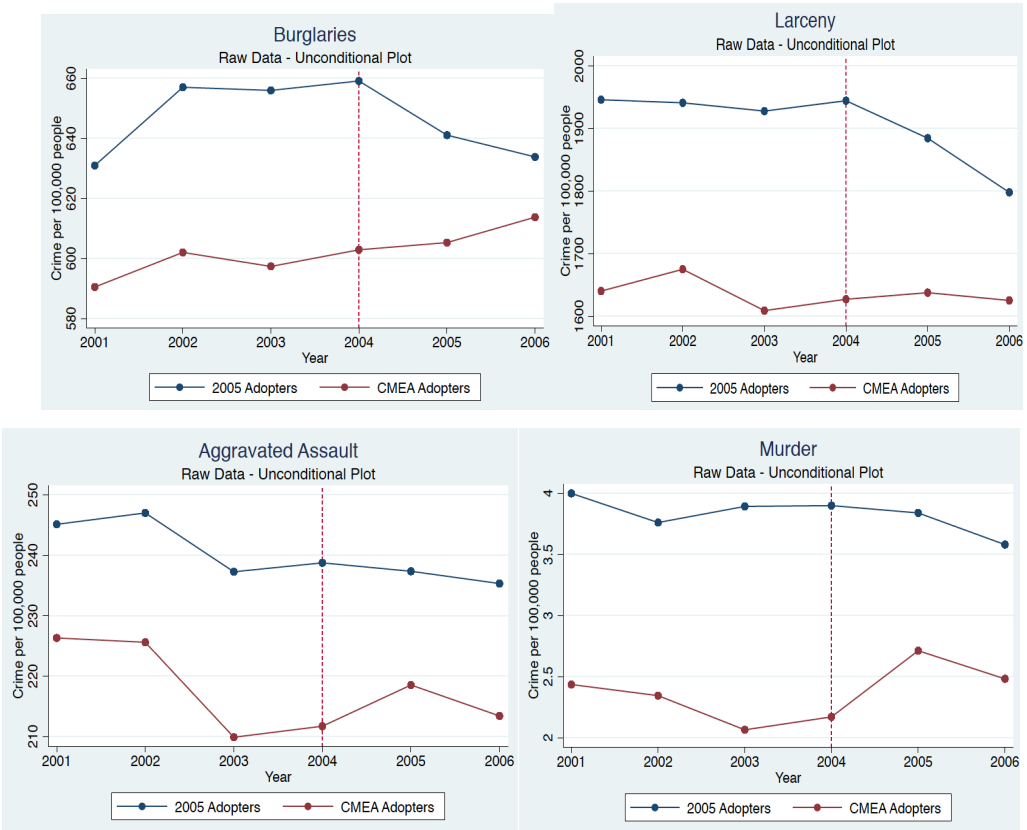
[80] Accessible at https://www.fbi.gov/stats-services/crimestats
[81] Tables are omitted for brevity considerations and are available upon request.

Figure 3: Map of US Restrictions Against Meth Chemical Precursors



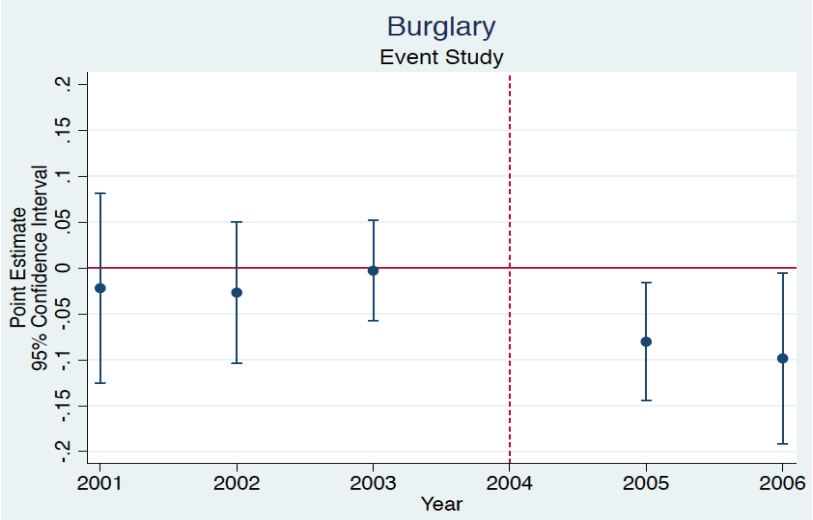
NOTES: This figure shows the year in which the first OTC restriction (either at the state or federal level) was enacted in each US State. Utah enacted a state regulation in 2001, followed by Oklahoma in 2004. The remaining states can be divided in three different groups: 1) ***Early adopters****, implementing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

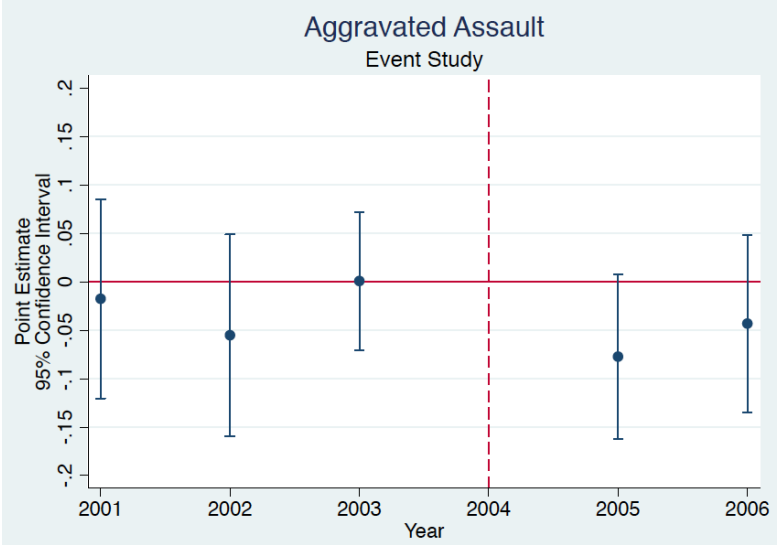
Figure 4: Graphical Analysis

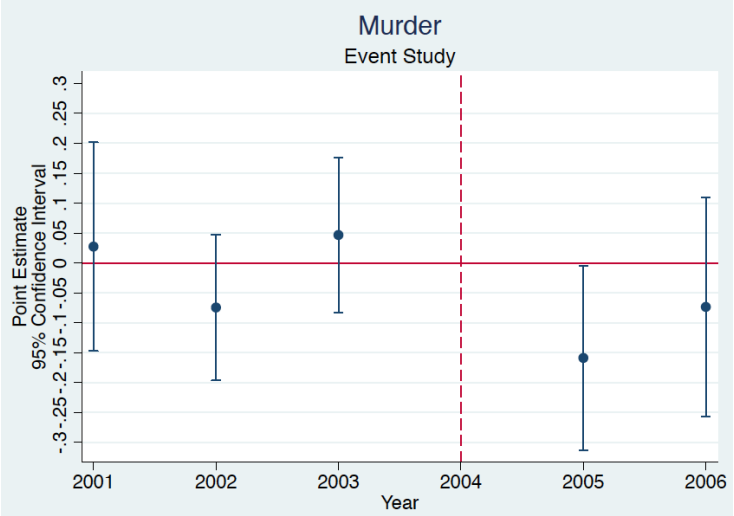


NOTES: This figure shows the evolution of larceny, burglary, aggravated assault and murder in states that adopted an internal regulation in 2005 ("2005 adopters") and in states where only the federal act CMEA was passed the 30th of September 2006 ("CMEA adopters"). For the case of murder I have excluded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

Figure 5: Event Study Analysis

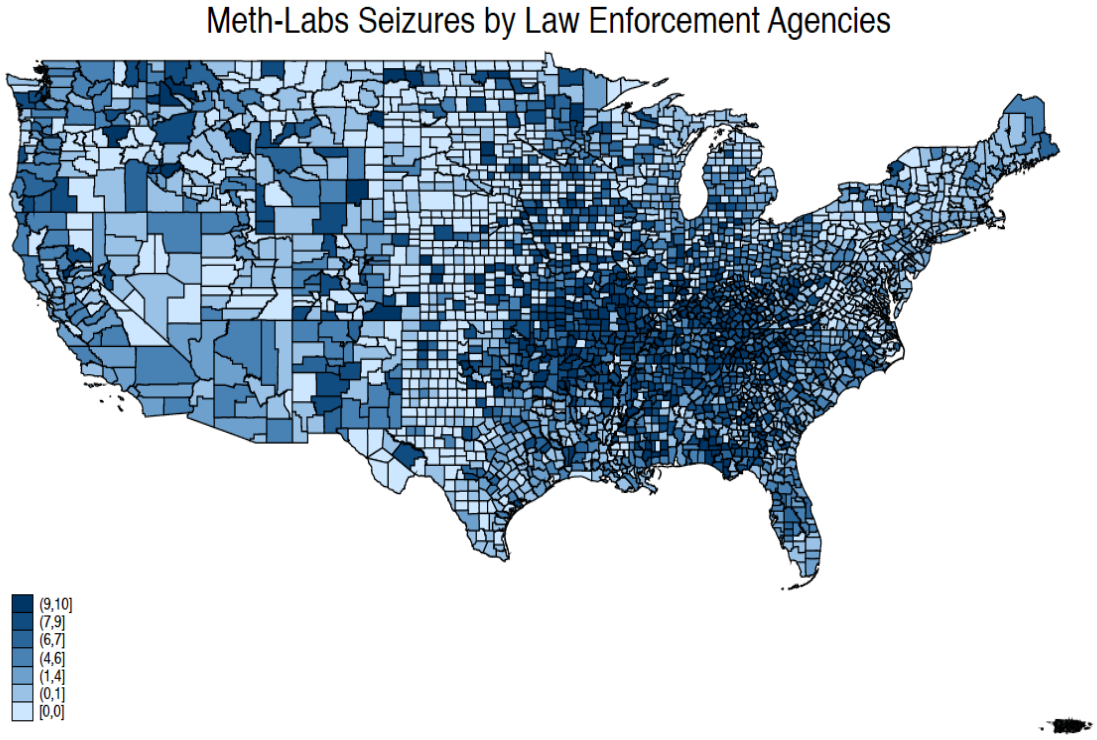






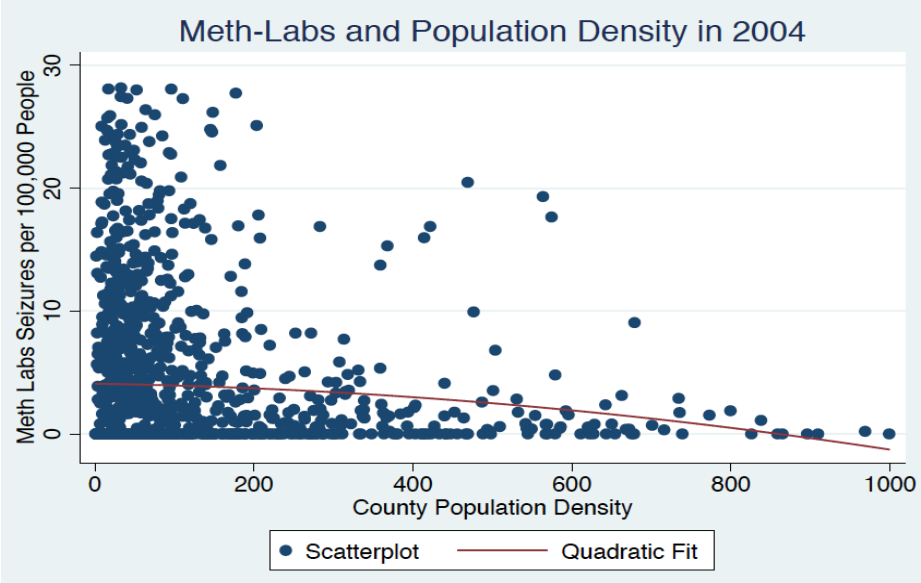
NOTES: This figure shows the plot of the coefficients obtained using the event study estimation as in equation (2) for burglary, larceny, assault and murder. Standard errors are clustered at the state level. The omitted category is the interaction between the two dummy variables "treated" and "year 2004".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

Figure 6: Map of Meth-Labs Seizures



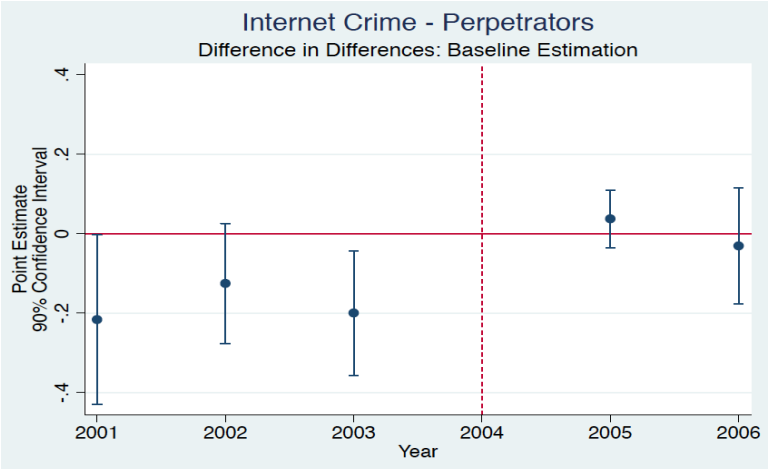
NOTES: This Figure shows the geographical distribution (expressed in deciles) of meth-labs seized by law enforcement agencies from 2004 to 2010. Alaska and Hawaii are eliminated from the figure for illustrative purposes only. Source (DEA, 2012).

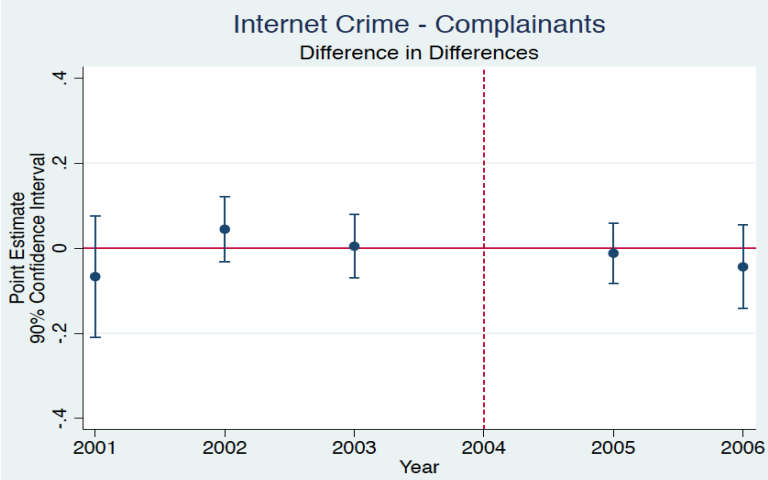
Figure 7: Meth-Labs and Population Density

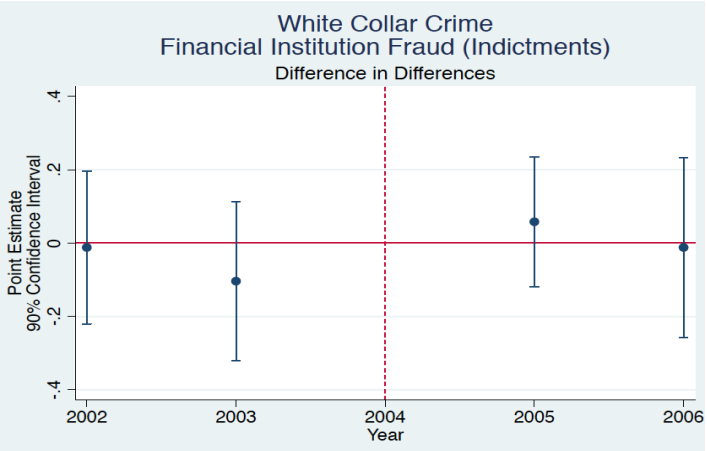


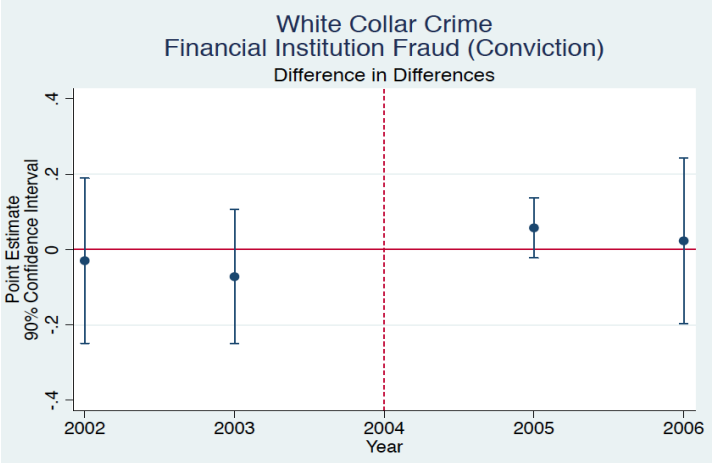
NOTES: This figure shows the scatterplot and the quadratic fit of the number ofmeth-labs seizured in 2004 in each county normalized per 100,000 people and the county population density in 2001. Both distributions are trimmed at the top 5% for illustrative purpose only.

Figure 8: Placebo Tests on Cyber and White-Collar Crimes









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

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

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

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

Table I–B
Pre-Intervention Differences, Criminal Activity

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

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

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

	(1) Control Counties	(2) Treated Counties	(3) Difference
Banks and commercial deposits	34.56	40.27	**-5.71*** **
Total deposits	1686258.58	1266475.58	**419783.00*** **
People below the poverty line	18547.59	19236.64	**-689.05*** **
Social security recipients	428.16	387.94	**40.22*** **
Density	1846.44	224.65	**1621.79*** **
Unemployment %	5.07	5.74	**-0.67*** **
Standardized measure of poverty	0.1	0.14	**-0.04*** **
Income per capital	32072.9	25477.1	**6595.80*** **
Police	2.46	4.27	**-1.80*** **
Police-Administrative	1.73	3.75	**-2.02*** **

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

TABLE II-A: Difference in Differences
Baseline Estimation

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

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

TABLE II-B: Difference in Differences
Baseline Estimation

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

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

precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with Post (a dummy that takes the value of 1 for 2005 and 2006 and 0 otherwise).

TABLE III: Robustness Check
Baseline Estimation + All County Observables

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

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

TABLE IV-A
Event study estimation

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

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

TABLE IV-B
Event study estimation

	(1) Robbery	(2) Rape	(3) Arson	(4) Vehicle Theft
Treated * 2001	0.101*	-0.0509	-0.0240	-0.0484
	(0.0583)	(0.0983)	(0.0758)	(0.0578)
Treated * 2002	0.0575	-0.0403	-0.0180	-0.0555
	(0.0685)	(0.0684)	(0.0725)	(0.0504)
Treated * 2003	0.0681	-0.104*	0.0735	-0.0319
	(0.0481)	(0.0606)	(0.0777)	(0.0400)
Treated * 2005	**-0.0520**	**-0.144***	**0.0530**	**-0.0463**
	(0.0508)	**(0.0761)**	**(0.113)**	**(0.0364)**
Treated * 2006	**-0.00849**	**-0.125**	**0.0697**	**-0.0647**
	(0.0783)	**(0.149)**	**(0.0923)**	**(0.0386)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.004	0.006	0.003	0.005
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

TABLE V-A: Robustness
Baseline + Police

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	-0.0426	-0.0300	-0.0244	-0.0353
	(0.0495)	(0.0525)	(0.0514)	(0.0744)
Treated * 2002	-0.0625**	-0.0255	-0.0527	-0.0744
	(0.0260)	(0.0386)	(0.0530)	(0.0627)
Treated * 2003	-0.0202	-0.00197	0.00243	0.0474
	(0.0286)	(0.0276)	(0.0362)	(0.0661)
Treated * 2005	**-0.102*** **	**-0.0798** **	**-0.0768* **	**-0.159* **
	(0.0306)	**(0.0325)**	**(0.0445)**	**(0.0790)**
Treated * 2006	**-0.128*** **	**-0.0991** **	**-0.0445**	**-0.0748**
	(0.0450)	**(0.0479)**	**(0.0474)**	**(0.0930)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.009	0.007	0.003	0.005
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

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

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2002	-0.0348	-0.00563	-0.0363	-0.0508
	(0.0260)	(0.0225)	(0.0479)	(0.0578)
Treated * 2003	-0.00829	0.00658	0.0104	0.0583
	(0.0286)	(0.0195)	(0.0294)	(0.0571)
Treated * 2005	**-0.119*** **	**-0.0894** **	**-0.0863* **	**-0.172* **
	(0.0361)	**(0.0412)**	**(0.0435)**	**(0.0981)**
Treated * 2006	**-0.159*** **	**-0.121**	**-0.0649**	**-0.0971**
	(0.0582)	**(0.0726)**	**(0.0636)**	**(0.132)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.034	0.027	0.021	0.009
Number of fips	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

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

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	-0.0435	-0.0281	-0.0283	-0.0393
	(0.0500)	(0.0529)	(0.0508)	(0.0752)
Treated * 2002	-0.0630**	-0.0248	-0.0559	-0.0749
	(0.0261)	(0.0387)	(0.0525)	(0.0630)
Treated * 2003	-0.0215	-0.00169	-0.000712	0.0488
	(0.0282)	(0.0276)	(0.0360)	(0.0664)
Treated * 2005	**-0.0969*** **	**-0.0756** **	**-0.0748* **	**-0.160* **
	(0.0288)	**(0.0313)**	**(0.0413)**	**(0.0795)**
Treated * 2006	**-0.122*** **	**-0.0940* **	**-0.0426**	**-0.0783**
	(0.0448)	**(0.0477)**	**(0.0469)**	**(0.0939)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.008	0.007	0.003	0.005
Number of Counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

TABLE V-D: Robustness
Linear Measure of Crime

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * 2001	3.126	-15.75	-8.901	-1.655*
	(50.11)	(22.15)	(9.316)	(0.847)
Treated * 2002	-35.80	0.308	-6.999	-0.350
	(32.90)	(17.04)	(11.26)	(0.305)
Treated * 2003	16.23	4.144	0.163	0.0475
	(28.57)	(10.73)	(5.419)	(0.258)
Treated * 2005	**-88.02*** **	**-22.94***	**-10.22***	**-0.597***
	(27.01)	**(13.77)**	**(5.596)**	**(0.349)**
Treated * 2006	**-176.6*** **	**-37.35**	**-4.329**	**-0.478**
	(48.80)	**(23.61)**	**(7.616)**	**(0.333)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.035	0.011	0.007	0.006
Number of Counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

TABLE V-E: Robustness
Fixed Effects Poisson Estimation

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

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

TABLE VI: Triple Difference in Differences
Population Density

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * Post	-0.0861**	-0.0898***	-0.0560	-0.129**
	(0.0397)	(0.0319)	(0.0534)	(0.0540)
Treated * Post* Density	0.00304	0.0179**	0.0148*	0.0394***
	(0.00469)	(0.00838)	(0.00844)	(0.00794)
Observations	9,585	9,585	9,585	9,585
R-squared	0.009	0.007	0.003	0.006
Number of counties	1,605	1,605	1,605	1,605
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

TABLE VII: Triple Difference in Differences
Meth-Labs Seizures Pre-Reform

	(1) Larceny	(2) Burglary	(3) Assault	(4) Murder
Treated * Post	-0.0846**	-0.0781**	-0.0300	-0.0804
	(0.0398)	(0.0351)	(0.0561)	(0.0624)
Treated * Post * Labs	-0.0132**	-0.00888	-0.0382**	-0.0482
	(0.00646)	(0.0107)	(0.0179)	(0.0438)
Observations	9,646	9,646	9,646	9,646
R-squared	0.009	0.007	0.003	0.005
Number of fips	1,618	1,618	1,618	1,618
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

Chapter IV – Drugs and Crime in the US: Exploring the Underlying Mechanisms

By ROCCO D'ESTE

This chapter investigates the mechanisms behind the reduction in crime. I detect a 38% reduction in operating meth-labs, no strong sign of relocation of criminal activity across states' borders, substitution in the demand or supply of other illegal substances, police crackdown on meth-abusers. I hence propose a simple theoretical framework that matches qualitative features of this market. I model the decision process of a typical "meth-head" hit by OTC restrictions via an unexpected crystal-meth price-shock. This framework guides and sharpens the interpretation of the results, providing an additional set of testable predictions, corroborated in the subsequent analysis. OTC restrictions led to: i) a drop in meth consumption, ii) an increase in meth-related hospitalizations associated with detox, withdrawal symptoms and rehab, iii) heterogeneous and non-monotonic effects on criminal activity across US states.

I. Estimating the Disruption of Meth Domestic Production

States regulations targeted the domestic production of crystal methamphetamines. To evaluate the effectiveness of these supply-side interventions, I include DEA data on the number of clandestine labs seized by law enforcement agencies. 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 Dobkin et al. (2014) discuss, 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. The following equation describes the relationship

between the differential percentage change in the number of labs detected and in the number of labs effectively operating:

$$\%\Delta(D_T - D_C) = \%\Delta(p_T - p_C)[1 + \%\Delta(L_T - L_C)] + \%\Delta(L_T - L_C) \quad (4)$$

Here $\%\Delta = \frac{post-pre}{pre}$, with post and pre referring to the period before and after the regulation, the subscripts T and C indicate treated and control states, D denotes the number of labs, p denotes the probability of detection and L denotes the "true" number of labs.

If the probability of detection is unaffected by OTC regulations ($\%\Delta p_t = \%\Delta p_c$) then the differential percentage change in the number of discovered labs represents an unbiased estimate of the reduction in the number of labs effectively operating.

Anecdotal evidence suggests that OTC laws slightly increased the probability that a given lab was detected in treated states post-regulations. In fact, some police departments might have visited the residences of people whose names appeared repeatedly in OTC sales logbooks. In this is so and ($\%\Delta p_t > \%\Delta p_c$), then using the percent change in the number of labs detected is likely to produce a *lower bound estimate* of the "true" reduction in the number of meth-labs.[82]

[Figure 9]

Figure 9 shows the total number of labs by year, with a decline of almost 50% from 2004 to 2005. The average number of methamphetamines labs seizures is 2.17 per 100.000 inhabitants with a standard deviation of 6.38.

[82] This line of reasoning applies only to the number of meth-labs but NOT to the quantity of methamphetamines produced.

Table VIII shows the result of estimating equation (1). The number of clandestine labs seized by law-enforcement agencies is available from 2004 onwards. I hence focus the analysis on the years 2004 to 2006. All the other details of this regression are the same as in estimating equation (1).

[Table VIII]

Column (1) shows 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. As shown in column (1), the introduction of the law reduces the number of meth-labs by 42%. The inclusion of county FE and all controls moves the estimates to -38%. Coefficients are precisely estimated with a significance level below 1%.

My point estimates are almost identical to those 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 22%, not significant at the 5 percent level.[83]

II. A Test for the Systemic Violence Hypothesis

The exit from the market of a multitude of meth-producers controlling low and medium capacity labs might have reduced the competition among drug dealers. This might have lowered the systemic violence associated with the sale of crystal methamphetamines. This dynamic might in part explain the drop in murders and aggravated assaults, detected in the first part 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

[83] Dobkin et al. (2014) estimated a 25% reduction in the domestic production of methamphetamines.

methamphetamines and 2) the number of homicides that occurred in circumstances related to gangs violence and illegal drug trafficking. For both specifications I use estimating equation (2).

Table IX, column (1) reports the results with outcome variable being arrests for sale of other dangerous non-narcotics.

[Table IX]

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.[84]

Despite the sharp reduction in the arrests for other dangerous non-narcotics, plausibly due to the drop in the domestic production of crystal methamphetamines and to the exit from the market of segments of unspecialized consumers/dealers, no significant change is detected on the violence associated with drug trafficking (expressed by homicides due to narcotic drug offense, gangland killings and juvenile gangs killings).

Table X 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 X]

I grouped homicide circumstances 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 (2). Results are shown in table XI.

[84] This result is robust to the inclusion of states-specific linear trends, with a coefficient of -30% in 2006, with an associated significance level below 5%. Results, omitted for brevity purpose only, are available upon request.

[Table XI]

I detect a reduction of 8.2% for 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 other homicide circumstances.

Overall, this analysis suggests that the reduction in violent crimes due to OTC restrictions do not seem to be driven by a reduction in the systemic violence, typically associated with the production/distribution of illegal drugs. This corroborates the ethnographic evidence on the segmentation of this market: extreme abusers decide to produce to have a cheaper access to the substance, rather then to extract profits from it.

This analysis – instead – supports the medical evidence on the violence enhancing effects of crystal-meth. OTC restrictions have reduced the episodes of violent altercations terminated with murder. These episodes might happen with higher probability when the offender is under the influence of this powerful neurotoxic drug (McKetin et al., 2014).

III. Geographical Spillovers Across Borders

I now investigate the presence of unintended consequences of OTC restrictions. This might be connected with the possible geographical relocation of meth production and associated criminal activity across states-borders. This hypothesis is tested using the following estimating equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + \sum_{j=2001}^{2006} (bordering * post)\,\beta_1 + \varepsilon_{c,s,t} \qquad (5)$$

I restrict this quasi-experimental design 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. I assign the value *bordering = 0* to non-bordering counties. Other details are identical to regression (1). Results are shown in table XII-A.

[Tables XII (A-B)]

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.

I then repeat the same exercise adopting a more flexible identification strategy. I use the distance of each control county to the closest treated county as continuous treatment intensity.[85] This leads to the following estimating equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + \sum_{j=2001}^{2006} (bordering * distance)\,\beta_1 + \varepsilon_{c,s,t} \qquad (6)$$

Results are shown in table XII-B. No significant effect is detected. This evidence, suggests that the crime reduction is not driven by a relocation of meth-production and criminal activity in control states, but rather by an effective drop in treated states.

[85] The matrix of distances between all counties can be freely accessed at the NBER page at the following link: http://www.nber.org/data/county-distance-database.html

IV. Drugs-Related Arrests

I now analyze the effects of OTC restrictions on the arrests for sale and possession of illegal drugs. This section investigates whether the drop in crime might be in part due to a specific effort of authorities in pursuing meth-abusers. Moreover, it also investigates the presence of potential spillovers across substances. OTC restrictions might have shifted both the demand and/or the supply-side towards other illegal substances.

The FBI categorizes drugs-related arrests in 4 different groups: other-dangerous non-narcotics (the category including crystal methamphetamines), synthetics narcotics (manufactured narcotics that can cause true drug addiction), marijuana and cocaine, opium and derivatives. Results, obtained using the event-study specification as in regression (2) are shown in table XIII-A (sale) and XIII-B (possession).

[Table XIII (A-B)]

No significant effect is detected in arrests for sale. The analysis of the coefficients nevertheless suggests a reduction for arrests of synthetics narcotics, after the enactment of the reform.[86] Table XIII-B reports the results for arrests for possession. Again, no significant coefficient is detected. Note that in 2005 we observe a coefficient of 0.12 with an associated p-value of 18% for the arrests of other dangerous non-narcotics. I further explore the relevance of this channel by including arrests for possession of other dangerous non-narcotics as a control variable in estimating equation (1). Results of the coefficient *treat*post* are

[86] This might be the case because several FBI agencies report the arrests for sale of methamphetamines in this category, rather then in the category of other dangerous non-narcotics. For example, CJIC collects drug arrest data submitted by police departments in Michigan who use the Michigan Incident Crime Reporting system (MICR). There are specific arrest codes for methamphetamine crimes. Michigan file class codes for possession arrests include the categories Methamphetamine Possession, Synthetic Narcotic (Other), and Synthetic Narcotic Possession. Synthetic Narcotic (Other) and Synthetic Narcotic Possession charges may include other drugs than methamphetamine that are synthetically manufactured, including MDMA (Ecstasy) and amphetamines (Michigan state police, 2007).

essentially identical to those obtained in the baseline specification. Overall, this analysis seems to indicate that the police crackdown on meth-users might be a factor in the reduction of criminal activity, but it is unlikely to explain it single handily.[87]

V. Summary of the Potential Mechanisms

The analysis of this section has provided the following insights: 1) OTC restrictions led to estimated 38% drop in the number of meth-labs, mainly driven by a reduction on small-medium capacity labs; 2) a decline in murders due to violent altercations, but no effect on homicides due to systemic violence; 3) no strong sign of relocation of criminal activity across borders, substitution in the demand or supply of other illegal substances, crackdown of police on meth-abusers.

VI. A Theoretical Framework

OTC restrictions, *de facto*, represent a price shock to segments of extreme abusers. Before the policy intervention they had access to crystal methamphetamines at low prices. This is either because they were meth-producers or because the substance was manufactured within their close network of acquaintances.

From a theoretical perspective, the impact of OTC regulations on crime is *ex-ante* ambiguous. 1) It could have led to an upsurge of appropriative crimes (as well as of violent crimes) committed by extreme drugs-addict to compensate for the increase in the cost of addiction. 2) An increase in prices – by negatively affecting consumption and potentially generating "cold turkey" episodes for

[87] Results are available upon request.

extreme abusers – might have reduced the proliferation of property crimes, (related to the need to support addiction or to foster small quantity productions), and/or both property and violent crimes (committed under the influence of this powerful substance).

In this section I propose a simple theoretical dynamic framework. This not only highlights the existence of the above-discussed tradeoff, but also aims at sharpening the interpretation of the empirical results. In fact, the model provides a further set of predictions. These are formally tested or explored using additional qualitative evidence.

VII. The Model

I set the model up to capture the qualitative features of the domestic market of crystal methamphetamines. I analyze the decision process of a typical "meth-head" hit by OTC restrictions.

I focus on a representative agent who has an initial stock of addiction S_0. The agent lives two periods: period 1 (pre-OTC restrictions) and period 2 (post-OTC restrictions). Each period, the agent decides how much crystal-methamphetamine to consume (M) – either by producing or by buying it – and how much crime to commit (C).

For tractability purpose, I assume that the agent commits crime only to get the money to sustain his drug habit and/or to foster the illegal production process. The budget constraint has the following form:

$$p_t M_t = C_t$$

Here p is the price of crystal methamphetamines and $t = 1,2$ indexes the time period. Consistently with ethnographic and DEA evidence about the typical

extreme meth-addict who turned into a producer, I do not embed a profit maximization problem within this theoretical framework. That is, the agent only cares about using the substance and needs to commit theft crimes in order to "get high".

A linear disutility is associated with committing criminal activity. There is a positive probability of apprehension from law-enforcement agencies: $\pi_1 = \pi_2 = \pi \in (0,1)$.

Assumption 1: $S_0 > \frac{\pi}{2}(p_1 + \delta E(p_2) + p_2)$

Here $\delta \in (0,1)$ is the agent's discount factor and $E(p_2)$ is date 1 forecast of date 2 prices. Assumption 1, while ensuring non-negative consumption and crime in both periods, captures the idea that the agent has a sufficiently high level of addiction. The agent hence may commit crime to finance his consumption.

In period 1 the agent suffers a quadratic loss when his consumption (M_1) deviates from his initial level of addiction (S_0):

$$U_1 = -(M_1 - S_0)^2 - \pi C_1$$

The choice of consumption in period 1 (M_1) affects the decision problem in period 2. The agents suffers a disutility that equals the quadratic distance between consumption across the two periods:

$$U_2 = -(M_2 - M_1)^2 - \pi C_2.$$

Assumption 2*: The agent is not perfectly forward looking (i.e. OTC restrictions represent an unexpected price shock to heavy users).*

Assumption 2 emphasizes how meth users developed their addiction before the period 1 reform. That is, when consuming and building up their habit, they did not internalize the possibility that prices would have dramatically increased in the future.

I explore the merits of assumption 2 using data on prices and purities of crystal methamphetamines. These 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). Price and purity estimates are derived from records in the STRIDE database. This is maintained by the Drug Enforcement Administration (DEA).[88]

[Figure 10]

Data on methamphetamines are expressed per pure gram for three different weight categories, highlighting three different levels in the illegal-drug distributional chain (0.1 – 10g, 10 – 100g and >100g). Quarterly prices in 2007 US dollars are aggregated at the national level.

Figure 10 reveals an interesting pattern on the evolution of prices of crystal methamphetamines (top panel). The vertical line represents the 3rd quarter 2005, when 70% of Early Adopters stated enacted OTC restrictions. Relative to the second quarter of 2005, the price for 1 gram of methamphetamines in quantities below 10 grams rose by 108%. The price for quantities between 10 – 100 grams rose by 70%. The price for quantities exceeding 100 grams rose by 55%.[89,90]

[88] 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

[89] Further evidence is provided by ethnographic studies. Lopez (2014) interviewed 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: "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

I solve the model recursively, giving the following optimal amounts of methamphetamines consumption and crime in the two periods:

Period 1 (Pre-Reform)

$$\begin{cases} M_1^* = S_0 - \dfrac{\pi\big(p_1 + \delta E(p_2)\big)}{2} \\ C_1^* = p_1\left(S_0 - \dfrac{\pi\big(p_1 + \delta E(p_2)\big)}{2}\right) \end{cases}$$

Period 2 (Post-Reform)

$$\begin{cases} M_2^* = S_0 - \dfrac{\pi}{2}(p_1 + \delta E(p_2) + p_2) \\ C_2^* = p_2\left(S_0 - \dfrac{\pi}{2}(p_1 + \delta E(p_2) + p_2)\right) \end{cases}$$

Proposition 1*: An increase in meth-prices monotonically decreases its consumption.*

Proof: By inspection,

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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 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).

[90] 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. The plot of prices and purity of crack-cocaine (figure XIII-A bottom panel), heroin and powder cocaine (figure XIII-B) does not reveal any significant pattern for these drugs.

$$\frac{\partial M_t}{\partial p_t} < 0, t = 1,2 \blacksquare$$

This model also captures the existence of a non-monotonic effect of a change in prices on criminal behavior.

Proposition 2*: The effect of an increase in meth prices on criminal activity exhibits an inverse U-Relationship with respect to the price level.*

In period 2 it can be shown that: [91]

$$\begin{cases} \frac{\partial C_2}{\partial p_2} > 0 \Leftrightarrow p_2 < \tilde{p}_2 \\ \frac{\partial C_2}{\partial p_2} \leq 0 \Leftrightarrow p_2 \geq \tilde{p}_2 \end{cases}$$

Where:

$$\tilde{p}_2 = \frac{2S_0 - \pi(p_1 + \delta E p_2)}{2\pi}$$

Proof: *Direct differentiation.* ■

A rise in meth prices makes addiction more expensive. Below $\tilde{p}_2$ this leads to an increase in criminal behavior. The expected marginal cost from crime is "somewhat acceptable" and it is less than the expected benefit deriving from meth consumption. Conversely, above $\tilde{p}_2$ the price of addiction becomes "too-high". This discourages criminal activity because the expected costs deriving from it exceeds its expected benefits.

[91] A similar reasoning applies for period 1.

Note that an increase in the initial level of addiction (S_0) pushes $\tilde{p}_2$ to the right: an extreme addict will resist more to an increase in prices before reducing his level of criminal activity. The opposite argument applies for an increase in the probability of apprehension π. This decreases the threshold-price $\tilde{p}_2$. Finally, an increase in p_1 *and* $E(p_2)$ will push the threshold to the left, by reducing meth consumption in period 1. This will indirectly produce less desire for the drug in the subsequent period, reducing criminal behavior. Proposition 3 offers the last theoretical prediction of the model.

Proposition 3: $\forall\, S_o\ \exists\, \bar{\bar{p}}_2\ such\ that\ p_2 > \bar{\bar{p}}_2 \implies C_2^* < C_1^*$

Proof:

$C_2^* > C_1^*$ Implies that:

$$\pi p_2^2 + p_2\left[\pi\left(p_1 + \delta E(p_2)\right) - 2S_0\right] + p_1\left[2S_0 - \pi\left(p_1 + \delta E(p_2)\right)\right] \leq 0$$

With $\pi > 0$ it is trivial to show that proposition 3 holds where the vertex of the parabola is below or above zero.■

This proposition highlights the possibility of heterogeneous and non-monotonic effects of the laws via a change in meth-prices. It also ensures that – independently from the initial level of addiction – there will always be a realized price p_2 above the threshold $\bar{\bar{p}}_2$ for which criminal activity in period 2 (post-regulation) falls below the level of criminal activity in period 1 (pre-regulation).

VIII. From the Model to the Data

This section explores and tests the empirical implications derived from the theoretical predictions of the model.

Testable Implication 1: *OTC restrictions reduced meth-consumption.*

A major drawback for this study is the lack of data on crystal-meth consumption. Nevertheless, figure 11 shows two informative separate pieces of descriptive evidence.

[Figure 11]

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

On the right hand side, I plot data from Drug Testing Index Archives of Quest Diagnostics, the largest provider of workplace drug tests in the US.[92] We observe a reduction of 15.2% in 2005 and 35.7% in 2006 with respect to the year 2004. The official documentation of Quest Diagnostics further corroborates Testable Implication 1:

[92] Freely available at http://www.questdiagnostics.com/home/physicians/health-trends/drug-testing/archives.html

"*Methamphetamine, the most commonly abused type of amphetamine, increased in production and trafficking during the 1990's to become the most prevalent illegally manufactured synthetic drug in the United States. Analysis of the Quest Diagnostics Drug Testing Index, released semi-annually, suggests that efforts to reduce illicit, clandestine production of methamphetamine may be having an impact on workplace positive tests for the drug".* [93]

The theoretical model – rather then focusing on the behavior of a low-frequency user – is built to analyze the decision process of segments of extreme abusers. These should have curbed the intensive/extensive margin of consumption, not without experiencing any physical or mental difficulty. This premise leads to testable implication 2.

Testable Implication 2*: OTC restrictions, by decreasing the intensive/extensive margin of consumption of extreme-abusers, have generated "cold turkey" episodes, meth-hospitalization due: to rehabilitation, detoxification and withdrawal symptoms.*

I formally test this hypothesis using the Treatment Episode Data Set (TEDS). This database is maintained by the Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration (SAMHSA). The TEDS system includes state level records for some 1.5 million substance abuse treatment admissions annually. While TEDS does not represent the total national demand for substance abuse treatment, it contains a significant proportion of all admissions to substance abuse treatment. These are voluntary admissions for detoxification, rehabilitation and ambulatory.

I use an estimating equation similar to equation (1). TEDS data and all socioeconomic controls are at the state-year level. Table XIV presents separate results for hospitalizations due to meth, alcohol, heroin, cocaine, marijuana, and amphetamines.

[Tables XIV]

Corroborating Testable Implication 2, I detect an increase of 34% for hospitalizations due to methamphetamines. This is significant at the 5% level. The effect is isolated only to crystal methamphetamines. No effect is detected on hospitalizations due to abuse of alcohol or other illegal substances.

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

[Figure 12]

Figure 12 shows national level data from 2004 to 2007. While we observe a general decrease in ED treatment throughout the US (top figure), we notice a peak in 2005 for emergency treatments for detox (+31% with respect to the pre-reform year in 2004). We also observe an increase in both 2005 and 2006 in emergency treatments due to suicides attempts connected with methamphetamine use. This is a condition medically associated with meth withdrawal (+20% in 2005 and +6.5% in 2006 with respect to year 2004).

Testable Implication 3: *OTC restrictions produce heterogeneous and non-monotonic (negative or positive) effects on criminal activity.*

I investigate the presence of potential heterogeneous impacts of the laws across US states. I estimate a regression of the following type:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + \sum_{j=1}^{30} (state\_treated_j * post)\,\beta_1 + \varepsilon_{c,s,t} \qquad (7)$$

I show the results of this specification in figure XI only for larceny and murder. I plot 30 states-specific coefficients obtained from a regression that interacts the variable "Post" with each state dummy.[94]

[Figure 13]

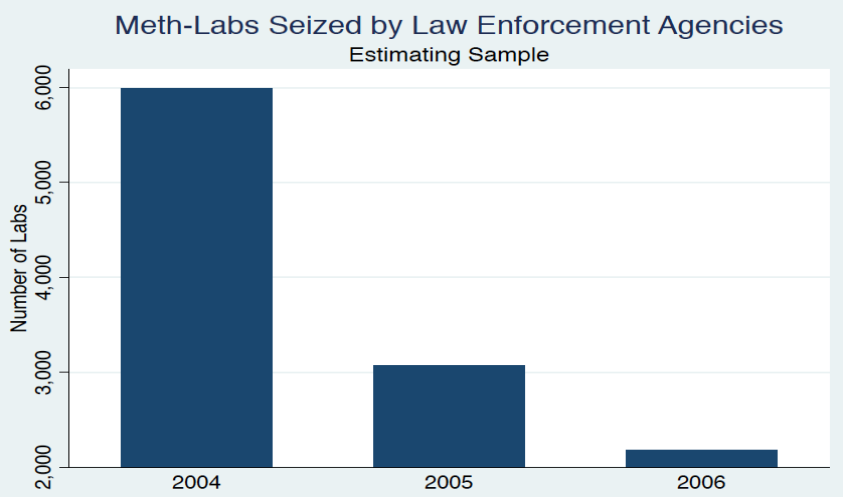
Figure 13 top-panel shows the plot of the coefficients for larceny and murder for each of the 30 treated states. This figure shows heterogeneous effects on both property and violent crimes. Four US states have seen a positive and significant effect on larceny due to OTC restrictions (Indiana, Missouri, Montana, Virginia, West Virginia) with Alabama, Louisiana and Hawaii displaying the top reduction. Three states display a significant increase in homicides (Arkansas, Delaware and Hawaii).

It is extremely difficult to investigate the specific causes behind this heterogeneity in the impact. I do an initial attempt plotting the same coefficients obtained from this regression (y-axis) and the log of the number of hospitalizations due to meth-abuse (figure 13 bottom panel). The graph shows negative correlations between the estimated coefficients and the normalized measure of predetermined meth-abuse at the state-level. This evidence suggests that the reduction in criminal activity is stronger in US states with a higher pre-determined concentration of extreme meth-addicts. Acknowledging the possible ambiguity of the impact on crime it is of absolute importance. Deepening the

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

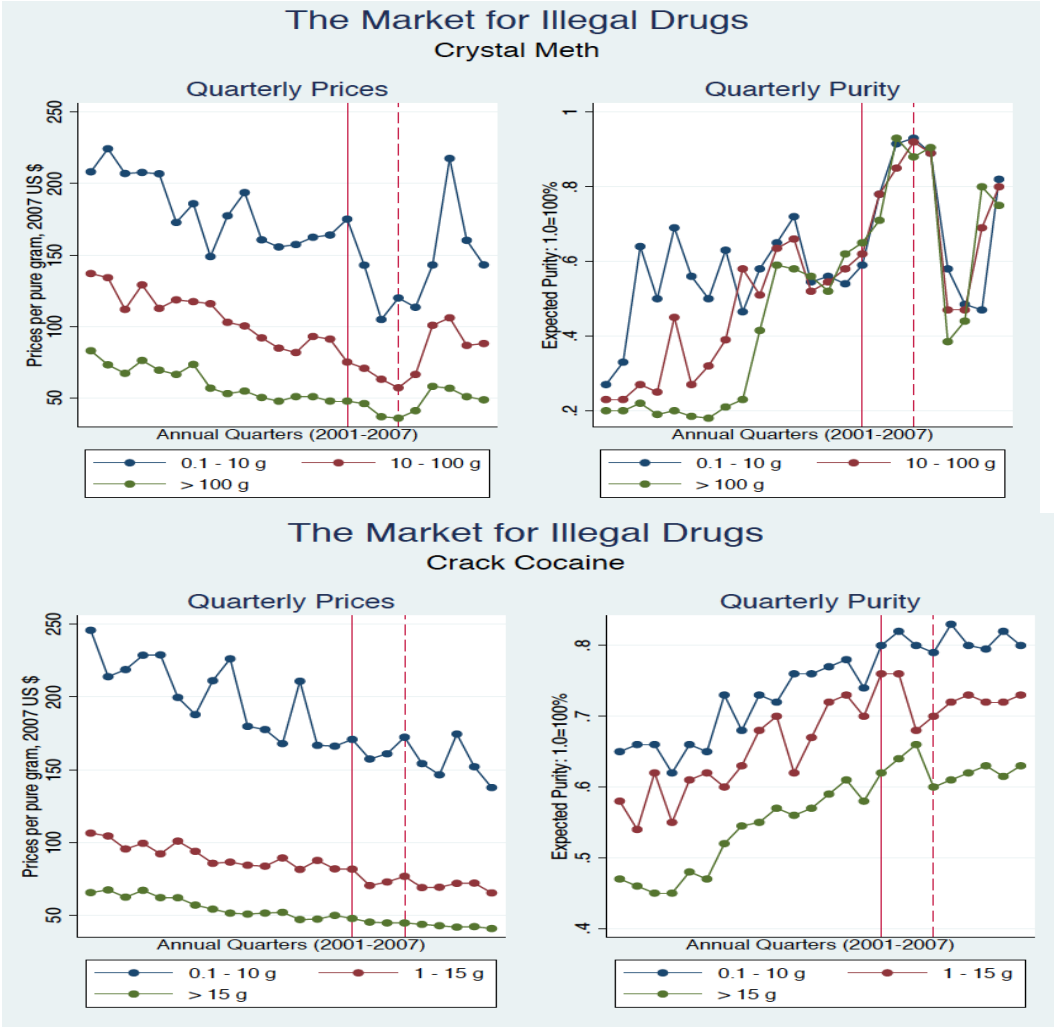
understanding of this heterogeneity represents a promising direction for future research.

Figure 9: Meth-Labs Seized in the United States, By Year



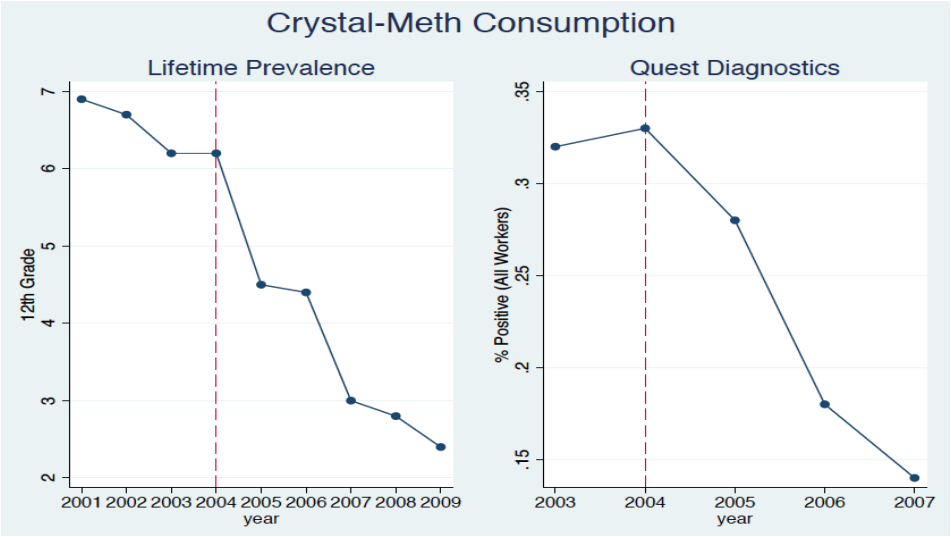
NOTES: This Figure shows the number of meth labs seized by law-enforcement agencies in all the United States, from 2004 to 2006. Source: (DEA, 2012).

Figure 10: Meth and Crack-Cocaine Prices and Purity



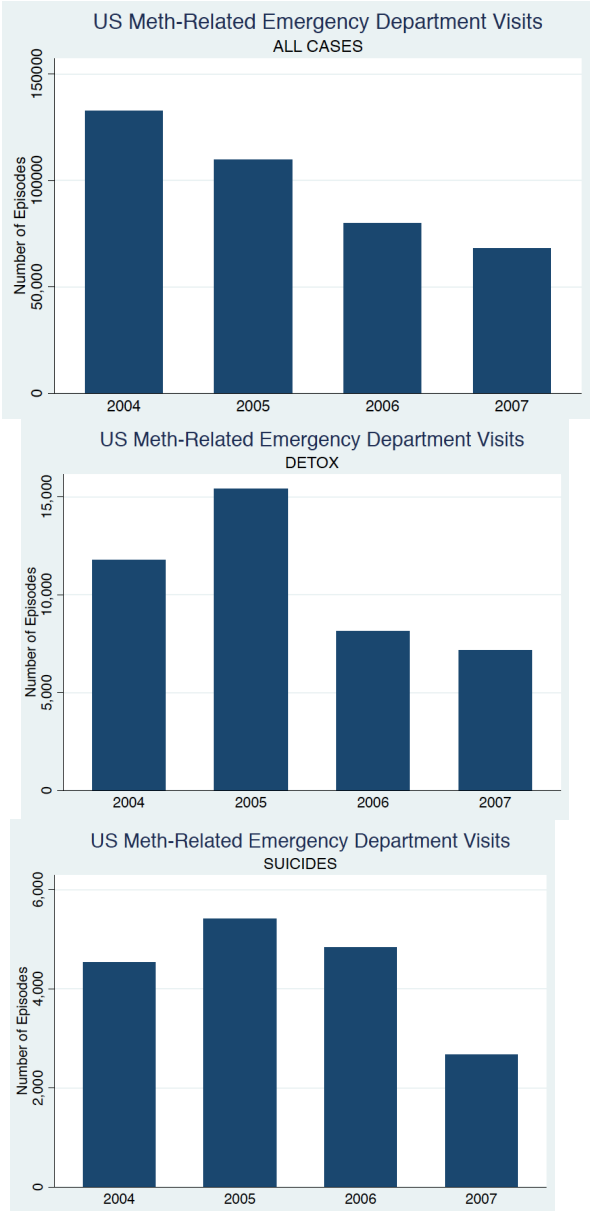
Notes: This figure shows the evolution of prices and estimated purities for crystal methamphetamines and crack cocaine. Data are obtained from the public report "The Price and Purity of Illicit Drugs" (2008) of the Institute for Defense Analysis (IDA) for the Office of National Drug Control Policy (ONDCP).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

Figure 11: Crystal Meth Consumption



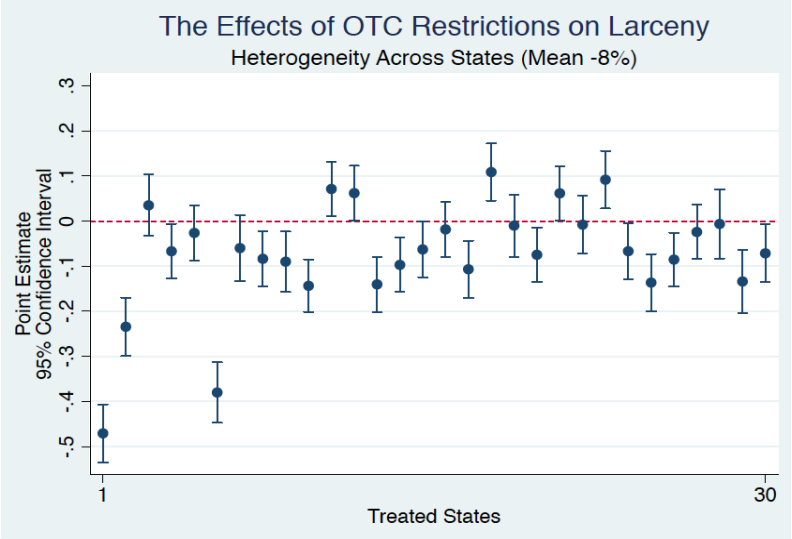
Notes: The top panel shows Regional Trends In Methamphetamines Reported per 100,000 people aged 15 and older. Source DEA (2014). The bottom panel shows the pattern of crystal meth consumption: lifetime prevalence (left-side) and work drug test (right-side). Sources: Monitoring the Future (University of Michigan) and Quest Diagnostics

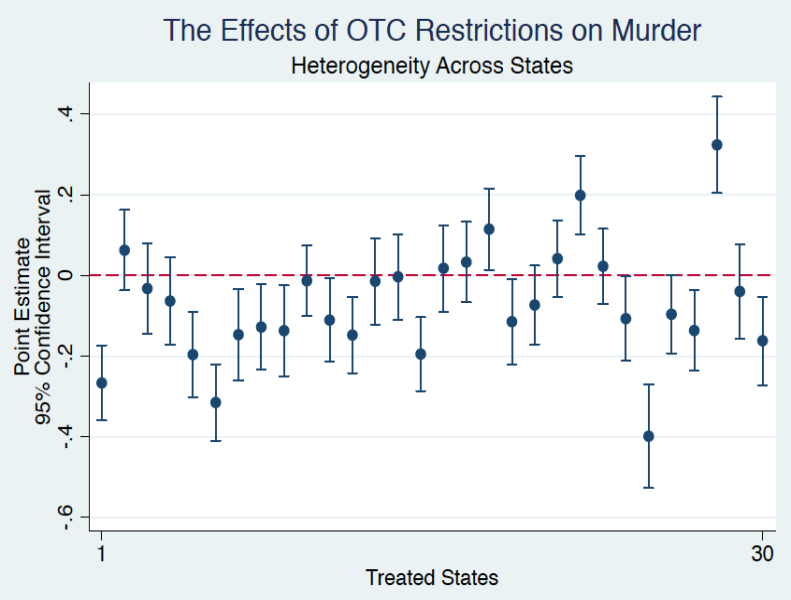
Figure 12: Meth-Related Emergency Hospitalizations

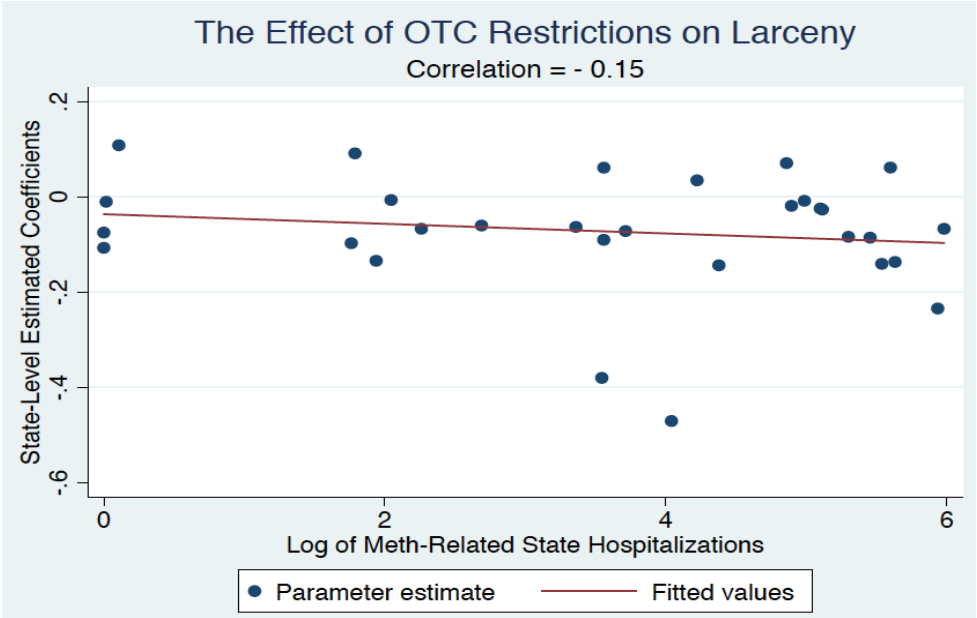


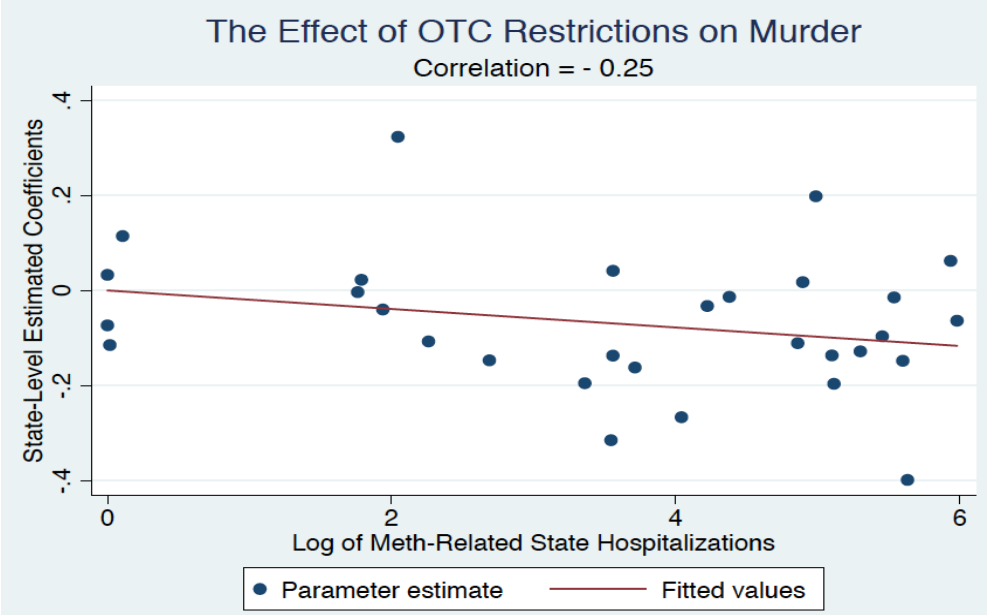
Notes: Source is the Drug Abuse Warning Network (DAWN). DAWN is a public health surveillance system that monitors drug-related emergency department (ED) visits in the United States and is a source for monitoring methamphetamine use. DAWN offers a unique perspective by examining use severe enough to warrant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

Figure 13: Heterogeneity of the Impact of OTC Restrictions, By US State









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

TABLE VIII
The Effect of OTC Restrictions on Meth-Labs Seizures

	(1) Baseline	(2) + County FE	(3) + County Observables
Treated * Post	-0.417***	-0.420***	-0.380***
	(0.0796)	(0.0795)	(0.0672)
Observations	4,846	4,846	4,829
R-squared	0.281	0.133	0.142
Year FE	YES	YES	YES
State FE	YES	NO	NO
County FE	NO	YES	YES
County Observables	NO	NO	YES
Number of counties	1,625	1,625	1,623

*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 all county observables.*

TABLE IX
Testing for Reduction in Systemic Violence

	(1) Arrests for Sale Other Dangerous non Narcotics	(3) Homicides due to Gangs and Systemic Violence
Treated * 2001	-0.409***	-0.0487
	(0.127)	(0.0396)
Treated * 2002	-0.156	0.0128
	(0.116)	(0.00760)
Treated * 2003	-0.000811	-0.00438
	(0.0789)	(0.0111)
Treated * 2005	**-0.0423**	**-0.00794**
	(0.101)	**(0.0156)**
Treated * 2006	**-0.230***	**0.00247**
	(0.114)	**(0.0141)**
Observations	9,664	9,664
R-squared	0.051	0.002
Number of fips	1,625	1,625
Year FE	YES	YES
County FE	YES	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 (2). I interact the variable treated (a dummy taking the value of 1 if the county belongs to a state that has regulated the provision of methamphetamine precursors chemicals in 2005 and 0 if it belongs to a state where only CMEA was implemented) with a dummy for each year (2001, 2002, 2003, 2004, 2005, 2006). The omitted category is the interaction between treated and the dummy for the year 2004 (the year before the enactment of the states laws. I also include county FE, year FE and all county observables. Outcomes are arrests for sale of other dangerous non-narcotics (column 1) and homicides due to gangs and systemic violence (column 2).*

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

TABLE XI: Difference in Differences
Homicides Circumstances

	(1) Theft	(2) Sex	(3) Violent Altercations	(4) Negligence
Treated * 2001	0.0440**	0.0200	-0.0798**	0.00172
	(0.0193)	(0.0228)	(0.0353)	(0.0125)
Treated * 2002	0.000848	0.0293*	0.00611	-0.0163
	(0.0251)	(0.0145)	(0.0406)	(0.0151)
Treated * 2003	0.0442*	0.0192	-0.00562	0.0115
	(0.0221)	(0.0223)	(0.0620)	(0.0133)
Treated * 2005	**0.00424**	**0.0124**	**-0.0822****	**0.0102**
	(0.0200)	**(0.0171)**	**(0.0383)**	**(0.0130)**
Treated * 2006	**-0.0334**	**0.000436**	**0.0167**	**-0.00411**
	(0.0308)	**(0.0142)**	**(0.0280)**	**(0.00811)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.004	0.002	0.003	0.004
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

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

TABLE XII-A
Geographical Spillovers in Control States: Binary Treatment

	(1) Meth-Labs	(2) Larceny	(3) Burglary	(4) Assault	(5) Murder
Border County * Post	0.0503	-0.0300	-0.0457	-0.00923	0.0857
	(0.0669)	(0.0323)	(0.0362)	(0.0498)	(0.103)
Observations	414	827	827	827	827
R-squared	0.069	0.037	0.074	0.049	0.039
Number of counties	138	138	138	138	138
Year FE	YES	YES	YES	YES	YES
State 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 county level. The level of observation is county – year. This table reports the results of a difference in differences specification for meth-labs seizures, larceny, Burglary Assault and Murder. I focus exclusively on counties in control states. I use the interaction of the variable "Border County" (a dummy taking the value 1 if the county shares the border with a treated state and 0 otherwise) with the "POST" dummy (years 2005 and 2006. The specification include year FE, state FE and all county observables. The sample goes from 2001 to 2006 included (2004-2006 for meth-labs seizures).*

TABLE XII-B
Geographical Spillovers in Control States: Continuous Treatment

	(1) Meth-Labs	(2) Larceny	(3) Burglary	(4) Assault	(5) Murder
Post * Distance to Closer Border	-0.0116	0.0150	0.0188	0.0237	-0.0300
	(0.0354)	(0.0136)	(0.0168)	(0.0230)	(0.0434)
Observations	414	827	827	827	827
R-squared	0.067	0.037	0.074	0.051	0.039
Number of counties	138	138	138	138	138
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 county level. The level of observation is county – year. This table reports the results of a difference in differences specification for meth-labs seizures, larceny, Burglary Assault and Murder. I focus exclusively on counties in control states. I use the interaction of the variable "Distance to closer border" (the distance in miles of each county to the closest county in a treated state) with the "POST" dummy (years 2005 and 2006. The specification include year FE, state FE and all county observables. The sample goes from 2001 to 2006 included (2004-2006 for meth-labs seizures).*

TABLE XIII-A
Arrests for Sale

	(1) Synthetics	(2) Marijuana	(3) Cocaine
Treated * 2001	-0.240	-0.308**	-0.133
	(0.162)	(0.136)	(0.104)
Treated * 2002	0.0411	-0.128	0.00173
	(0.115)	(0.0806)	(0.0712)
Treated * 2003	0.0334	0.0732	0.0566
	(0.105)	(0.0683)	(0.0559)
Treated * 2005	**-0.0957**	**-0.0703**	**-0.0707**
	(0.0728)	**(0.0599)**	**(0.0762)**
Treated * 2006	**-0.202**	**0.0214**	**-0.0541**
	(0.128)	**(0.108)**	**(0.0801)**
Observations	9,664	9,664	9,664
R-squared	0.006	0.006	0.020
Number of counties	1,625	1,625	1,625
Year FE	YES	YES	YES
County FE	YES	YES	YES
County Observables	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 arrests for sale of Other Dangerous non-narcotics (the FBI Category including Meth) 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 all county observables*

TABLE XIII-B
Arrests for possession

	(1) Other	(2) Synthetics	(3) Marijuana	(4) Cocaine
Treated * 2001	-0.276	-0.211	-0.307*	-0.283***
	(0.211)	(0.176)	(0.158)	(0.100)
Treated * 2002	0.0408	-0.0698	-0.0311	-0.0708
	(0.175)	(0.135)	(0.0627)	(0.0802)
Treated * 2003	-0.00574	-0.230*	0.0290	-0.112*
	(0.0759)	(0.132)	(0.0549)	(0.0650)
Treated * 2005	**0.125**	**-0.0171**	**0.0681**	**-0.0291**
	(0.0861)	**(0.0820)**	**(0.0664)**	**(0.0618)**
Treated * 2006	**-0.0818**	**-0.141**	**0.0577**	**0.104**
	(0.136)	**(0.101)**	**(0.0640)**	**(0.115)**
Observations	9,664	9,664	9,664	9,664
R-squared	0.099	0.068	0.026	0.056
Number of counties	1,625	1,625	1,625	1,625
Year FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
County Observables	YES	YES	YES	YES

*Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the state level. The 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 arrests for possession of Other Dangerous non-narcotics (the FBI Category including Meth) 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 all county observables.*

TABLE XIV
TEDS Hospitalizations

	(1) Meth	(2) Alcohol	(3) Heroin	(4) Cocaine	(5) Marijuana	(6) Ampheta mines
Treated * Post	**0.341****	0.0317	0.000987	-0.0118	0.0669	-0.0555
	(0.160)	(0.0409)	(0.0863)	(0.0900)	(0.0475)	(0.187)
Observations	224	224	224	224	224	224
R-squared	0.324	0.104	0.117	0.171	0.102	0.071
Number of states	38	38	38	38	38	38
Year FE	YES	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES	YES
State Observables	YES	YES	YES	YES	YES	YES

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

Chapter V – Drugs and Crime in the US: IV Design and Other Results

By ROCCO D'ESTE

This final chapter aims to estimate the elasticity of crime to meth-labs. I use a combination of diff-in-diff and IV designs. First, I present the baseline empirical strategy and related results. Then, I discuss potential threats to identification, proposing and implementing alternative approaches. These aim to reduce concerns related to the violation of the exclusion restriction. Finally, I present: i) an additional DD design exploiting a subsequent federal act, ii) the examination of the long-run effects of OTC restrictions.

I. An Instrumental Variable Design

In this section I address the endogenous entry/exit or opening/closing of meth-labs. I use states' OTC restriction as an instrumental variable for the county-level measure of meth-labs. This is approximated by law-enforcement seizures. Equation (9) shows the first stage regression. Equation (8) reports the two-stage least squares estimating equation:

Two stage least squares:

$$y_{c,s,t} = \alpha_s + \delta_t + X'_{c,s,t}\beta_0 + \widehat{meth\_labs}_{c,s,t}\beta_1 + \varepsilon_{c,s,t} \qquad (8)$$

First stage:

$$meth\_labs_{c,s,t} = \gamma_s + \eta_t + X'_{c,s,t}\beta_2 + (treat * post)\beta_3 + \zeta_{c,s,t} \quad (9)$$

Data on meth-labs seizures are available from 2004. I limit the analysis from 2004 to 2006. The instrument is the interaction of the treated dummy and the dummy post (which

is 0 in 2004 and 1 in 2005 and 2006). Reported crimes and meth-labs are expressed as $ln(1+x)$. Here x is the relevant variable expressed per 100,000 inhabitants. The baseline specification includes state FE rather than county FE, due to the availability of only three years of data. County FE are added in the subsequent robustness check. Socio-economic controls are also included.

[Table XV]

Results of the first stage regression are reported in table XV 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 XVI-A and XVI-B report the results of the OLS and IV specifications. Table XVI-A reports the results on theft crimes (larceny, burglary and motor-vehicle thefts). Table XVI-B reports the results for violent crimes (murder, aggravated assaults and rapes).

[Tables XVI (A-B)]

For property crimes, the elasticity on larceny and burglary is 0.25 and 0.3 significant, in both cases, at the 1% level. The elasticity 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, 0.18 for assault and 0.36 for murder. All these coefficients are precisely estimated at the 1% or 5% significance level.

II. Potential Threats to Identification Via IV Design

The close inspection of the coefficients shows that IV estimates are three to five times larger than OLS for both violent and property crimes. The only exception is murder. IV estimates are 30 times larger than OLS.

Discussion

Part of this gap could be rationalized by idiosyncratic and systematic measurement error. This inevitably derives from using meth-labs seizures as a proxy for the underlying covert production of methamphetamines. Measurement error generates attenuation bias in the OLS estimates. Chalfin and McCrary (2014) present evidence on the importance of this issue in the basic dataset on police used in the U.S. literature, the Uniform Crime Reports (UCR). They show that prior regression-based estimates are too small by a factor of four or five.[95] This is consistent with the results included in this section.

The IV design estimates the local average treatment effect (LATE) rather than the average treatment effect (ATE). Hence, LATE > ATE might suggest that OTC restriction targeted significantly more low-quantity labs. These were run by segments of extreme abusers that – before regulations – were plausibly responsible for a great deal of criminal activity.[96]

The validity of the identifying assumption relies on the absence of any effect of the instrument on the outcome running through some omitted variable. OTC restrictions should affect crime only via a meth-labs reduction, conditional on the controls used in the analysis. Consequently, it is important to recognize that IV > OLS could be a signal that the exclusion restriction is violated. The reduced-form might not capture confounders positively correlated with the outcome variable of interest.

While it seems hard to imagine that OTC regulations, (controlling the access to common medicines exclusively via quantity limits, sales environment constraints, proof of identification and logbooks), might have affected criminal activity trough other

[95] 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.

[96] A third 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.

channels rather then the exit from the market of dangerous clandestine meth-labs, there might be potential threats to the validity of the exclusion restriction.

As already discussed, one potential threat relates to a change in the effort of police officers or agencies in cracking down dangerous meth-addicts. Moreover, big US producers could have flood the market with low-quality crystal meth. They could have done this either to extract profits from the new situation or to compensate the reduced availability of chemical precursors. This reduction in quality is shown in figure XIII-A) could have pushed segments of extreme abusers to reduce consumption and associate criminal behavior.

Alternative Strategy

County-level data on specific police effort and on purity of crystal meth are not available. However, to reduce the concerns that one of these potential general equilibrium effects might be playing a major role in the estimation, I implement the following strategy:

1) *I exclude from the estimating sample the set of treated counties that do not belong to the two top quintiles of the pre-determined distribution of meth-labs seizures in 2004.* In this excluded sample it seems more likely that other confounding factors, rather then the closing of meth-labs (which were already very few) might have played an important role in the reduction in crime. Plausibly, these low-producing counties could have been exponentially affected by the flooding in the market of low-quality meth produced in US big labs.

2) Using this sample of counties, I include a set of "bad" controls conceivably able to absorb unobserved confounding general equilibrium effects. These are: arrests for sale and possession of other dangerous non-narcotics (which is a proxy for the police effort of crackdown on meth abusers), the number of police officers with arrests powers and with administrative duties, and the number of hospitalizations due to meth-abuse.

[Figure 14]

Figure 14 shows the quintiles of a uniform distribution of meth-labs seizures in 2004 (top panel) and the relative Kernel density estimate (bottom-panel), exclusively for counties belonging to treated states. The distribution of meth-labs seizures is positively skewed, with a median of 0.36, a mean of 6.07 and a standard deviation of 12.6. This denotes a great concentration of meth-labs in few counties within treated states.

[Tables XVII (A - B)]

Tables XVII-A and XVII-B show the OLS and IV results for property and violent crimes, respectively. This specification includes all counties in control states. As explained, I only include treated counties in the top 2 quintiles of the pre-determined distribution of meth-labs seizures in 2004. The first stage of this specification is stronger (-1.3 significant at the 1% level) with an F of the excluded instruments of 745.

IV estimates show an elasticity of .05 to .1 significant for the case of larceny, burglary, rape, assault and murder. IV estimates are significant at the 1% level. These estimates are lower than the ones obtained in the full sample, effectively suggesting the presence of potentially unobserved GE effects. The distance between OLS and IV does not exceed 1.3, with the only significant exception being rape.

Table XVIII shows the IV regressions (again performed in the restricted sample of all controls and high-producing counties). This includes county FE and potentially "bad controls" already discussed.

[Table XVIII]

The magnitude of the estimates is reduced by around 20% but remains statistically significant at the 1% for burglaries and larceny, at the 5% for murder and rape and at the

10% for aggravated assault.[97]

Overall, despite the difficult challenge to isolate the effects of clandestine labs on criminal activity, these estimates suggest that meth-labs have a direct effect on the propagation of criminal activity. This is quantifiable within an elasticity range of 0.1 to 0.3.

III. Other Results

The CMEA Federal Act: A Further Experimental Design

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*.[98]

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.* 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 (2) and it is defined by the following equation:

$$y_{c,s,t} = \alpha_c + \delta_t + X'_{c,s,t}\beta_0 + \sum_{j=2001}^{2010}(CMEA * year_j)\,\beta_{1,j} + \varepsilon_{c,s,t} \qquad (10)$$

[97] Chalfin and McCrary (2014) provide a review on the effects of police, punishment and legal market opportunities on crime, with a particular focus on papers from the last 20 years. This is useful to benchmark the estimated elasticity of meth-labs with other factors causing crime. Crime's elasticity to unemployment is responsive is large for property crimes, less for violent crimes (1 to 6). For wage it falls within the interval (-0.3 to -0.9 for property and violent crimes). For prison population it lies within the interval (-0.1 to -0.7). Finally, the implied elasticity of sentence length is -0.5.

[98] 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, and Wisconsin.

I 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 15 shows the plot of the coefficients with the 95% confidence interval for larceny, burglary, aggravated assault and murder. Similarly to estimating equation (2) 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. Standard errors are clustered at the state level.

[Figure 15]

For larceny (top-left corner) coefficients are significantly positive in 2005 and 2006. These are the years in which *Early Adopters* states enacted OTC regulations. This reflects the already discussed decline in crime in *Early Adopters* states due to OTC regulations implemented in 2005. A small and insignificant drop is observed in the year 2007. The coefficients are again significantly positive in 2009 and 2010.

The analysis suggests the presence of some persistence in the effects of OTC regulations on larceny in *Early Adopters* states, but no significant effects in *CMEA Only* states. Coefficients associated with all the other crimes are not precisely estimated.[99]

The absence of a significant effect might be reconciled with several explanations. From an econometric perspective, equation (1) 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, low levels of domestic meth production, as shown in table III, characterized CMEA Only states. The legislation regulating methamphetamines had hence no impact on crime. Third, because of this reason, CMEA Only states might have paid less attention to the effective implementation of these laws.

[99] Results are not reported for brevity considerations only and are available upon request.

The Long Term Impact on Crime of OTC Restrictions

In this empirical strategy, I include All US states in the analysis. I use the staggered implementation of the laws to examine the presence of the long run effects of OTC restrictions on crime.

[Figure 16]

The plot of the coefficients is shown in figure 16. The figure reveals a drop in crime after OTC restrictions. Coefficients are not precisely estimated.

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 often the same across states, both in terms of years and specific dates. Excluding Oklahoma and Utah, all the other states have implemented a law either in 2005 or in 2006. 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 estimation.

IV. Concluding Remarks

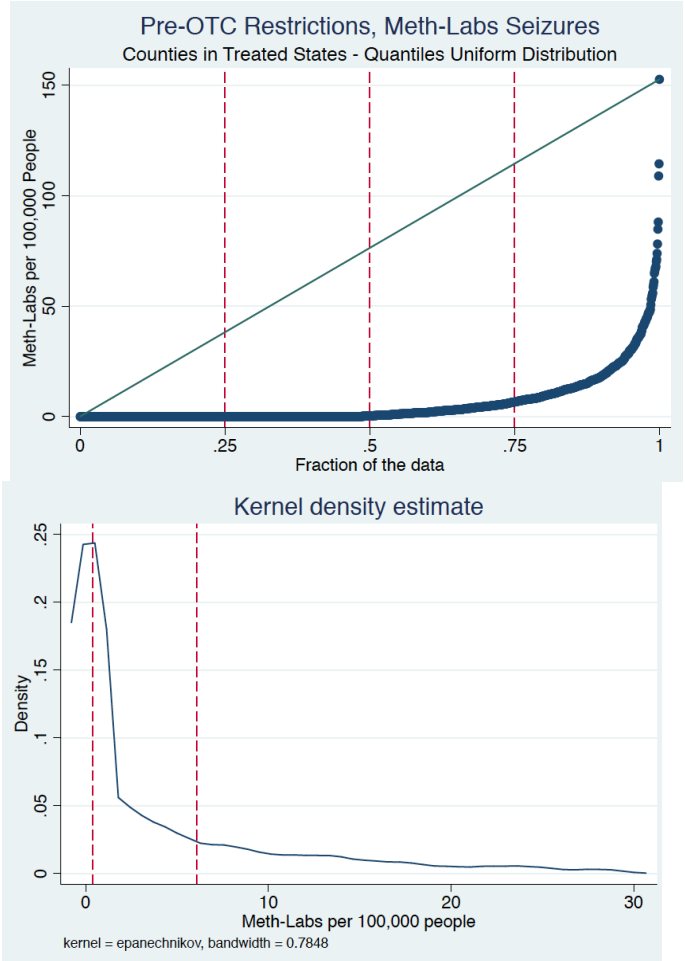
Chapters III, IV and V offer one of the first systematic empirical investigations of the effects of the markets for illegal drugs on crime. Motivated by the richness of anecdotal evidence, I look at crystal methamphetamine, a neurotoxic powerful substance widely diffused in the United States. To address endogeneity concerns – (in the attempt to break the simultaneity circle connecting drug's abuse and criminal propensity) – I use OTC restrictions as a source of exogenous variation. These limited the access to methamphetamine's chemical precursors. These were used by extreme meth-addicts to

sustain their habit and the habits of their close network of acquaintances.

Using a reduced-from DD design, I find that these regulations led to detect a sharp drop in property and violent crimes within the range of 5% to 10%. The analysis of the underlying mechanisms has provided the following insights: 1) a 38% drop in the number of meth-labs, mainly driven by a reduction on small-medium capacity labs; 2) a drop in murders due to violent altercations, but no effect on homicides due to systemic violence; 3) no strong sign of relocation of criminal activity across borders, substitution in the demand or supply of other illegal substances, crackdown of police on meth-abusers.

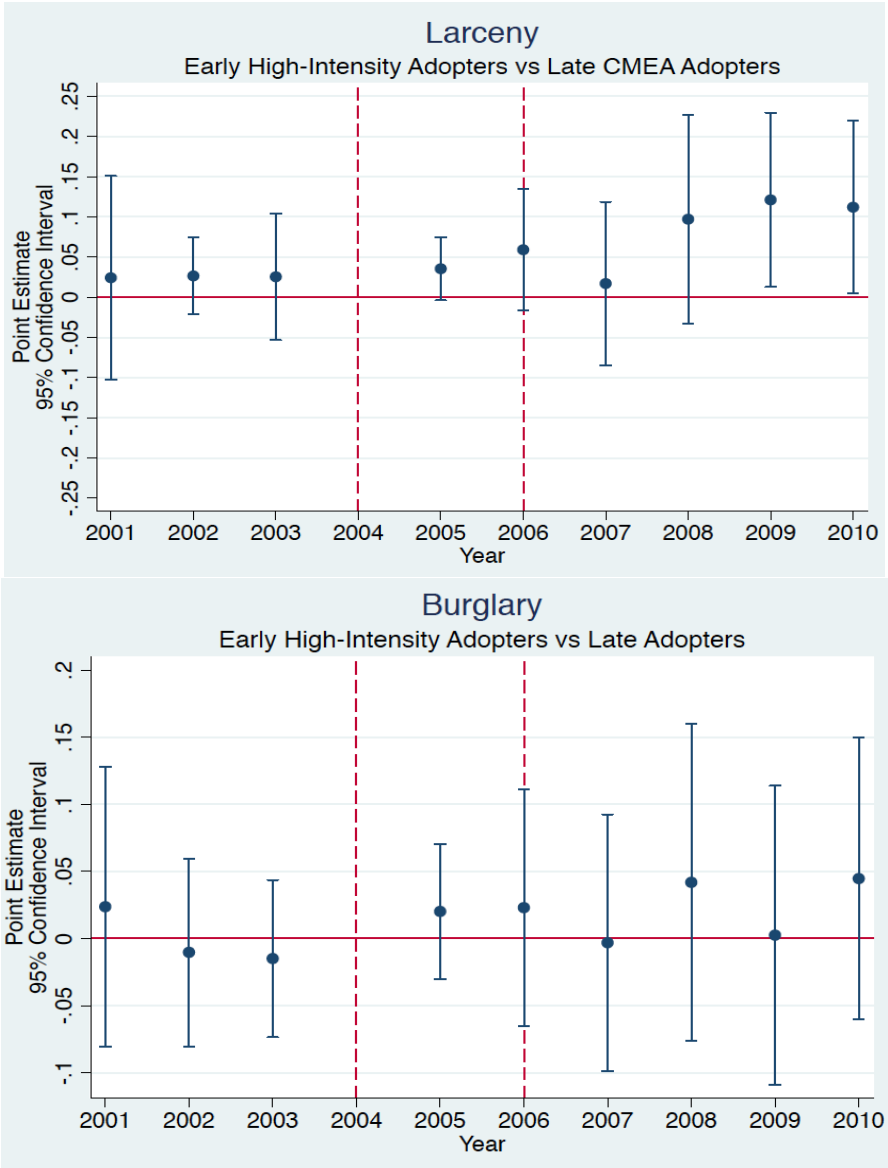
Overall, this paper supports the hypothesis that OTC restrictions impacted criminal activity mainly via the reduction in the intensive/extensive margin of consumption of segments of extreme meth-addicts. These are typically characterized by high criminal propensity when under the influence of this powerful substance. This work ultimately suggests that embedding the criminogenic effects deriving from illegal drugs' abuse within the cost-benefit analysis developed in Becker (1968), can provide a richer framework through which analyzing criminal behavior's production function.

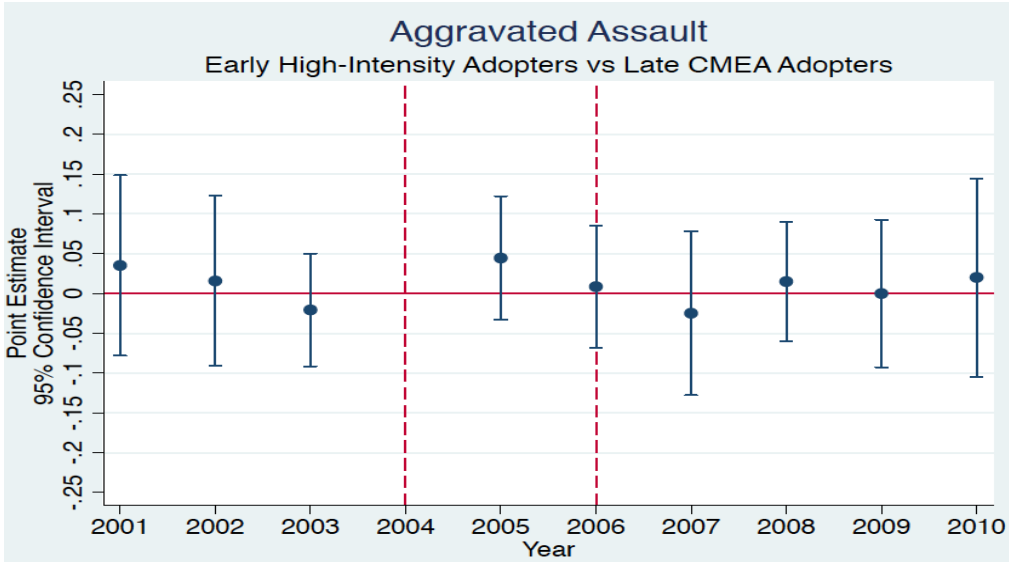
Figure 14: Kernel Density Meth-Labs Seizures

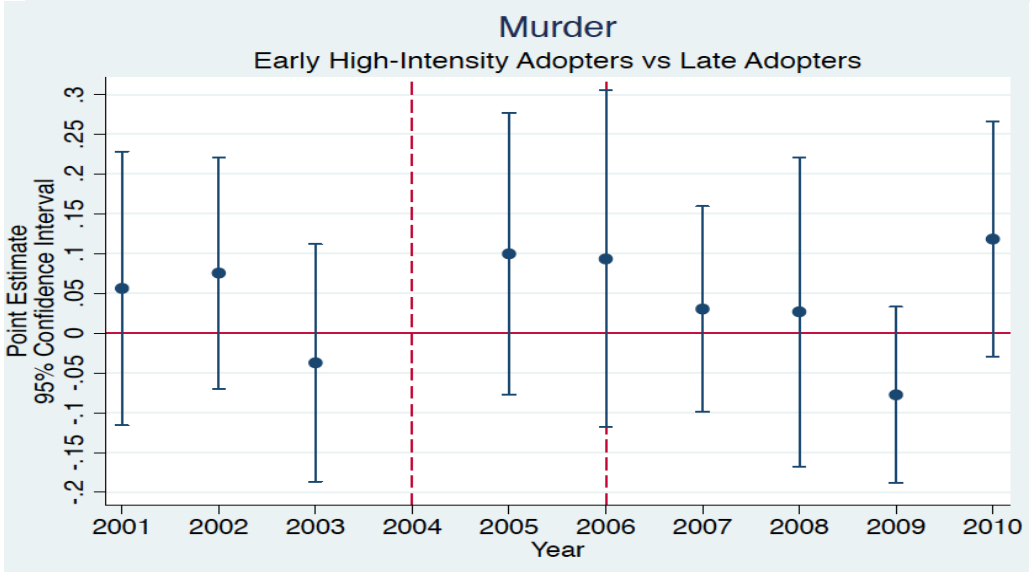


NOTES: This figure shows the quantiles of a uniform distribution of the meth-labs seized by law-enforcement agencies in each county in 2004. Labs are normalized per 100,000 people.

Figure 15: CMEA Federal Act As An Additional Experimental Design

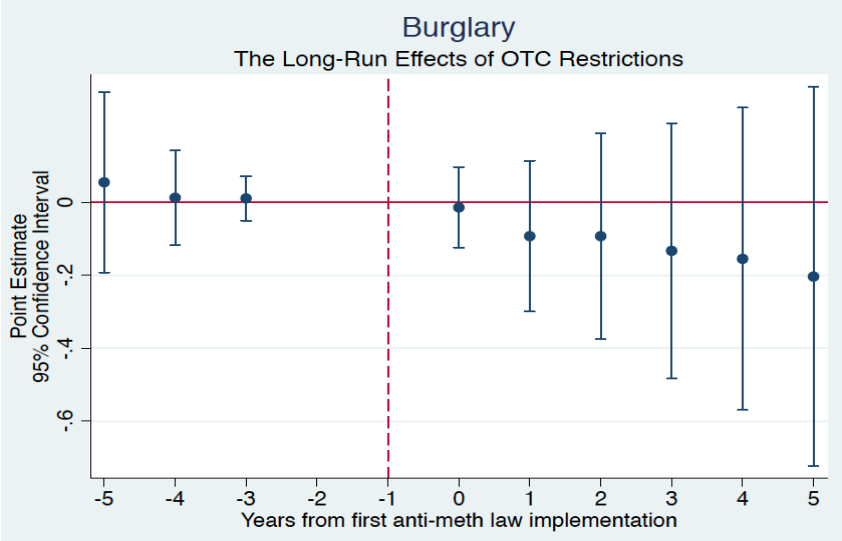


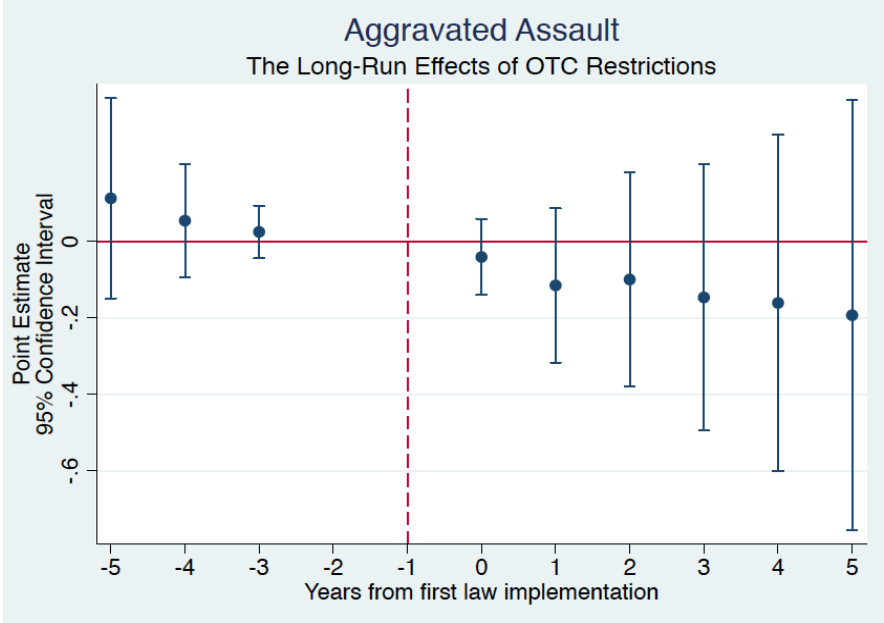




NOTES: This figure shows the plot of the coefficients with the 90% confidence interval using estimating equation (10) for larceny, burglary, aggravated assault and murder. I use the following estimating equation: $y_{i,s,t} = \alpha_i + \delta_t + X'_{i,s,t}\beta_0 + \sum_{j=2001}^{2010}(CMEA * year_j)\,\beta_{1,j} + \varepsilon_{i,s,t}$ *. 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 16: The Long Run Effects of OTC Restrictions





NOTES: This figure shows the plot of the coefficients of a regression with dummies indication the years to/from the implementation of the first OTC restriction in each state. Crime is expressed as the log normalized measure of crime per 100,000 inhabitants and standard errors are clustered at the state level.

TABLE XV (First-Stage)
The Effect of OTC Restrictions on Meth-Labs Seizures

	(1) Baseline	(2) + County FE	(3) + County Observables
Treated * Post	-0.417***	-0.420***	-0.380***
	(0.0796)	(0.0795)	(0.0672)
Observations	4,846	4,846	4,829
R-squared	0.281	0.133	0.142
Year FE	YES	YES	YES
State FE	YES	NO	NO
County FE	NO	YES	YES
County Observables	NO	NO	YES
Number of counties	1,625	1,625	1,623

*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 all county observables.*

TABLE XVI-A: OLS-IV Regressions
Sample of all counties – Property Crimes

	(1)	(2)	(3)	(4)	(5)	(6)
	Larceny		Burglary		Vehicle Theft	
	OLS	IV	OLS	IV	OLS	IV
Meth-Labs	0.0648***	0.248***	0.0464***	0.224***	0.0734***	0.112
	(0.0167)	(0.0557)	(0.0147)	(0.0602)	(0.0174)	(0.0702)
Observations	4,829	4,829	4,829	4,829	4,829	4,829
R-squared	0.169	0.138	0.188	0.153	0.296	0.295
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
County Observables	YES	YES	YES	YES	YES	YES
F-Stat		105.54		105.54		105.54

*Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the county 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.*

TABLE XVI-B: OLS-IV Regressions
Sample of all counties – Violent Crimes

	(1)	(2)	(3)	(4)	(5)	(6)
	Rape		Assault		Murder	
	OLS	IV	OLS	IV	OLS	IV
Meth-Labs	0.0597***	0.341**	0.0331**	0.185***	0.0136	0.360**
	(0.0209)	(0.135)	(0.0161)	(0.0674)	(0.0173)	(0.144)
Observations	4,829	4,829	4,829	4,829	4,829	4,829
R-squared	0.189	0.147	0.311	0.292	0.172	0.075
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
County	YES	YES	YES	YES	YES	YES
Observables		105.54		105.54		105.54
F-Stat						

*Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the county level. The level of observation is county – year. This table reports the results of both the OLS and IV specification for Rape, 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.*

TABLE XVII-A: OLS/IV Regression
Focus on top 40% Meth-producing Counties in Treated States

	(1)	(2)	(3)	(4)	(5)	(6)
	Larceny		Burglary		Vehicle Theft	
	OLS	IV	OLS	IV	OLS	IV
Meth-Labs	0.0654**	0.120***	0.0557**	0.0997***	0.0650***	0.0459
	(0.0256)	(0.0254)	(0.0235)	(0.0248)	(0.0252)	(0.0302)
Observations	2,188	2,188	2,188	2,188	2,188	2,188
R-squared	0.211	0.209	0.229	0.227	0.345	0.345
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
County Observables	YES	YES	YES	YES	YES	YES
F-Stat		745		745		745

*Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the county 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. I restrict the sample to the top 40% treated counties in the distribution of meth-labs seizures in 2004 and to all control counties.*

TABLE XVII-B: OLS/IV Regression

Focus on top 40% Meth-producing Counties in Treated States (Pre Intervention)

	(1)	(2)	(3)	(4)	(5)	(6)
	Rape		Assault		Murder	
	OLS	IV	OLS	IV	OLS	IV
Meth-Labs	0.00795	0.129***	0.0556**	0.0902***	0.0509**	0.134**
	(0.0309)	(0.0473)	(0.0246)	(0.0274)	(0.0241)	(0.0521)
Observations	2,188	2,188	2,188	2,188	2,188	2,188
R-squared	0.188	0.179	0.333	0.332	0.208	0.202
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
County Observables	YES	YES	YES	YES	YES	YES
F-Stat		754		754		754

*Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the county level. The level of observation is county – year. This table reports the results of both the OLS and IV specification for Rape, 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. I restrict the sample to the top 40% counties in the distribution of meth-labs seizures in 2004 and to all control counties.*

TABLE XVIII: IV Estimation (Top 40%)
Robustness to County FE and Potentially "Bad" Controls

	(1) Larceny	(2) Burglary	(3) Vehicle Theft	(4) Murder	(5) Assault	(6) Rape
Meth-Labs	0.0930***	0.0799***	0.0183	0.0972**	0.0536*	0.134**
	(0.0253)	(0.0264)	(0.0340)	(0.0474)	(0.0321)	(0.0578)
Observations	2,188	2,188	2,188	2,188	2,188	2,188
Counties	731	731	731	731	731	731
Year FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
County Observables	YES	YES	YES	YES	YES	YES
F-Stat	580	580	580	580	580	580

*Notes: ***, **, * Denote statistical significance at the 1%, 5%, 10% level respectively. Robust standard errors, reported in parenthesis, are clustered at the county level. The level of observation is county – year. This table reports the results of the IV specification. 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. I restrict the sample to the top 40% counties in the distribution of meth-labs seizures in 2004. I also include county FE, arrests for sale and possession of other dangerous non narcotics (the FBI category including crystal methamphetamines) and the state level number of hospitalizations due to meth-abuse.*

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