The War on Drugs: Estimating the Effect of Prescription Drug Supply-Side Interventions

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Abstract

This paper estimates the effect of supply-side interventions on prescription drug availability, abuse, and crime. I employ novel data and exploit the timing and geographic location of a crackdown on legal suppliers of pharmaceuticals in Florida, the epicenter of America's prescription drug abuse epidemic during the late 2000s. Between 2010-12, nearly 600 pain clinics were shut down. In turn, average oxycodone quantities decreased 59%, oxycodone street prices increased 238%, opioid abuse treatment admissions increased 33%, and approximately 2,000 oxycodone-related deaths were averted. Spillovers from substitution of prescription drugs with illegal drugs were modest, with approximately 139 new heroin-related deaths and no increase in crime.

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Prescription drug abuse is America's fastest growing drug problem.[1] In 2013, an estimated 6.5 million Americans aged 12 or older reported being non-medical users of prescription drugs in the past month, more than any other illicit drug except for marijuana (Substance Abuse and Mental Health Services Administration, 2014). Opioids, used medically to relieve pain, are the most commonly abused prescription drugs. Between 1999-2010, opioid pain reliever sales increased fourfold (Paulozzi et al., 2011). At the same time, opioid pain reliever overdose deaths increased by 313%, from 4,030 to 16,651, exceeding those involving heroin and cocaine combined (Centers for Disease Control and Prevention, 2015). The rates of neonatal abstinence syndrome, substance abuse treatment admissions, and emergency department visits involving the non-medical use of opioids have likewise all increased (Patrick et al., 2012; Paulozzi et al., 2011; Substance Abuse and Mental Health Services Administration, 2013).

Reducing drug abuse and its associated harms is an important policy goal of the federal government, which may control drug consumption with interventions that target either the demand or the supply of drugs.[2] The question of supply-side intervention effectiveness is especially relevant, as this approach receives the bulk of federal government drug control spending. Yet, there is considerable debate regarding its value at the margin. Multiple studies have failed to find substantial and sustained effects of increases in enforcement in the market for illegally-produced drugs.[3] Findings from previous studies, however, may not generalize to prescription

[1] When alluding to prescription drug abuse, I refer to the non-medical consumption of the subset of prescription drugs that is regulated under the Controlled Substances Act.

[2] Prevention and treatment are demand-sided and seek to deter the consumption by new and existing users. Source country control, interdiction, and domestic enforcement are supply-sided, and seek to increase the cost of supplying drugs, thereby raising retail prices and reducing consumption.

[3] DiNardo (1993); Weatherburn and Lind (1997); Yuan and Caulkins (1998); Miron (2003); Kuziemko and Levitt (2004); Dobkin and Nicosia (2009); Crane and A. Rivolo (1997); Dobkin et al. (2014); Cunningham and Liu (2003)

drugs. While the pharmacological effects of prescription and illegal drugs often resemble each other (e.g. euphoria, addiction, etc.), prescription drugs have accepted use in medical treatment, and can thus be produced and dispensed legally. Moreover, supply-side interventions of legally-produced drugs can include enforcement through administrative action and other regulatory solutions.

Survey data suggests that most diverted prescription drugs are produced by legal suppliers, as doctors are patients' original source.[4] In 2013, 23% of past year non-medical users reported obtaining opioid pain relievers from doctors, and 46% reported obtaining them for free from a friend or relative who obtained them from doctors (Substance Abuse and Mental Health Services Administration, 2014).[5] Knowingly or not, healthcare providers play an important role in the diversion of prescription drugs, and thus targeting pharmaceuticals' legal supply-chains might yield different results.

This paper estimates the effect of enforcement efforts against diverting healthcare providers on prescription drug availability, abuse, health, and crime. To the best of my knowledge, this is the first systematic study of supply-side intervention effectiveness in the context of prescription drugs.[6] The study focuses on Florida, the

[4]Prescription drugs are diverted from their legitimate sources when they are sold and consumed outside the scope of their intended medical purpose.

[5]The breakdown is: drug dealers/ stranger (4.3%); Internet (0.1%); other (4.4%); doctors (23.8%); bought/ took from friend or relative (14.6%); and free from friend or relative (53%). Those in the latter category report their friend or relative obtained the drugs from doctors 87% of the times.

[6]There is a growing literature on the effectiveness of methods to address prescription drug abuse, most of which is descriptive or focuses on prescription drug monitoring programs. Note that simultaneous to this study, Johnson et al. (2014) released a short CDC report describing the situation in Florida and focusing on deaths and prescriptions. Results from their study coincide with those from this study. Also, Dobkin et al. (2014) study supply-side interventions in a somewhat related context but their focus is on over-the-counter drugs, which are much less regulated. I focus on the enforcement and regulation of controlled prescription drug suppliers.

epicenter of America's prescription drug abuse epidemic during the late 2000s.[7] The main source of drug diversion was physicians who, supported by distributors and pharmacies, dispensed and prescribed oxycodone and other pharmaceuticals from pain clinics or "pill mills." In mid-2010, law enforcement and legislative officials initiated a sweeping crackdown on Florida's pill mill suppliers. There were two key aspects to this intervention: (1) Physicians could no longer dispense prescription drugs;[8] and (2) Diverting suppliers had their state medical license/ Drug Enforcement Administration's Certificate of Registration suspended, revoked, or denied, and could no longer handle prescription drugs.

An effective supply-side intervention should decrease quantities and increase prices. I begin the analysis by examining these outcomes in the market for prescription drugs. As the intended policy goal is to reduce prescription drug abuse and its associated harms, I also examine prescription drug-related deaths, hospitalizations, and substance abuse treatment admissions. A shock to legal suppliers need not reduce overall drug abuse if it generates spillovers into the market for illegal drugs. Specifically, substitution with illegal drugs and criminal activity could rise and offset the intended effects of the supply-side intervention. To shed light on this issue, I conclude the analysis by examining illegal drug consumption, crime, and drug arrests. Data on outcomes are collected from novel online and administrative sources. In this way, I overcome the well-known data constraint of quantifying supply and number of suppliers in underground markets faced by illegal drug studies.[9] The identifica-

[7]In 2009, Florida pharmacies and doctors dispensed nearly 3 and 265 times more oxycodone grams per capita than the average state (ARCOS).

[8]Note that prescribing and dispensing are different concepts. The former orders the use of a medication, while the latter delivers such medication. Note also that under these changes, physicians could still prescribe or administer drugs as long as their DEA registration/ state medical license was active.

[9]This paper uses prescription drug quantity and supplier data, which identifies supply and suppliers by state, healthcare provider, and active ingredient, and allows tracking supply recovery

tion strategy is to exploit variation in the timing and geographic location of the crackdown.

Florida's crackdown on legal suppliers resulted in the closure of many pain clinics. From 988 active pain clinic licenses in June 2010, only 407 remained active by the end of 2012. During this period, oxycodone street prices increased 238%, and average quantities decreased 59%, the largest state-level shock to oxycodone supply in over a decade.[10] There are no substantial supply spillovers across states, suppliers, or other opioid pain relievers.[11] Supply reductions were accompanied by declines in indicators of non-medical opioid pain reliever consumption. Specifically, deaths and hospitalizations decreased substantially. Similar trends are observed for benzodiazepines, which are often co-abused with opioids. Meanwhile, substance abuse treatment admissions with a mention of opioids and benzodiazepines increased by 33% and 42%, respectively. There is no evidence of an oxycodone price, supply, or consumption recovery, at least up to three-and-a-half years post-crackdown, which contrasts with results from most illegal drug studies where supply-side interventions have, at best, a short-run effect.[12]

There was some substitution to heroin, which is consistent with a recent nationwide spike in heroin overdose deaths anecdotally attributed to initial opioid pain reliever abuse (Jones et al., 2015). Although heroin deaths and hospitalizations display high post-crackdown growth, the magnitude of this offsetting effect is small relative to substantial public health gains from decreases in oxycodone deaths and hospitalizations. Other illegal drugs appear to be unaffected. This shift in the mar-

and spillovers.

[10]Note that supply data are available up to 2013, but for consistency across datasets regression analysis is restricted up to 2012.

[11]There is evidence of modest spillovers in Georgia (see Section A.3 for details).

[12]Florida's Medical Examiners report that in 2014 oxycodone deaths continued to decline, and so, for this measure the effect persists up to four and a half years.

ket for legal and illegal drugs did not result in a rise in criminal activity. If anything, there is weak evidence of a slight decrease in drug arrests and index crimes. More robust evidence is found for supplier-reported drug theft, which declined by 40%.

The success of the intervention is likely due to a number of supply and demand factors. From the supply side, high entry costs in the market for prescription drugs arising from technological barriers and stringent federal regulation might facilitate production to be contained among legal suppliers. This could explain why legal rather than illegal suppliers are the original source of most diverted prescription drugs.[13] In this setting, incapacitating suppliers could be more effective because legal suppliers are observable, and if diverting at a large scale, might be easier to identify and remove from the market. Moreover, deterrence effects could be large considering that legal suppliers operate in healthcare markets and it might be difficult for doctors to openly price discriminate against non-medical users or increase legal prices in response to a higher probability of apprehension.[14] From the demand side, the general belief that prescription drugs are "safer" to consume (Arria et al., 2008) and access possibly deterred some non-medical users from switching to heroin, opting instead for substance abuse treatment.

While new opportunities for prescription drug diversion might eventually become available and increasing heroin consumption might eventually reach oxycodone levels,[15] findings from this study suggest that at least in the medium-run, supply-side interventions can be an effective policy tool in the war against prescription drug abuse, especially in the face of an epidemic.

[13]There is a small number of illegal suppliers producing rogue oxycodone pills based on other active ingredients.

[14]Legal prices might be difficult to increase if these are determined by the government, insurers, or pharmaceutical companies.

[15]Florida's Medical Examiners report that in 2014 heroin deaths continued to increase in Florida.

1 Background

1.1 Prescription Drug Abuse

In 2011, the Centers for Disease Control and Prevention classified prescription drug abuse in the U.S. an epidemic. The development of new drug therapies, prescribing practices, expansion of insurance coverage, pharmaceutical advertisement, and increased availability have contributed to the problem (National Center for Health Statistics, 2015). The most commonly abused prescription drugs include central nervous system (CNS) depressants, stimulants, and in particular, opioid pain relievers.[16]

Drugs within the opioid class bind to the opioid receptors and may cause side effects such as sedation, respiratory depression, and euphoria. With continued use, physical and psychological dependence can develop, leading to withdrawal with abrupt discontinuation. Opioids are often snorted or injected and co-abused with benzodiazepines, a type of CNS depressant, to enhance the high (Jones et al., 2012). Oxycodone, a schedule II opioid and the active ingredient in the commonly prescribed medications Percocet and Oxycontin, is favored among non-medical users for its euphorigenic effects (Cicero et al., 2013). In 2013, the U.S. share of global oxycodone consumption stood at 78% (International Narcotics Control Board, 2014). Opioid pain reliever sales have increased dramatically over the last decade and so have the social costs associated with their abuse.[17]

The social costs of drug abuse comprise the internal and external costs of health,

[16] In 2013, an estimated 70% of Americans aged 12 or older who reported being non-medical users of prescription drugs in the past month, also reported using opioid pain relievers (Substance Abuse and Mental Health Services Administration, 2014).

[17] (Birnbaum et al., 2011) estimate that in 2007 the social costs of prescription opioid abuse amounted to $55.5 billion. Healthcare, criminal justice and workplace costs accounted for 45%, 9% and 46% of total costs, respectively.

crime, and labor productivity losses. Health costs include those from morbidity and mortality, and the healthcare expenditures incurred in addressing their harm. The prevalence of these costs in the context of opioid pain relievers is well documented: overdose deaths involving opioid pain relievers increased by 303% from 4,030 in 1999 to 16,235 in 2013 (Centers for Disease Control and Prevention, 2015); emergency department visits increased by 183% from 172,738 in 2004 to 488,004 in 2011 (Substance Abuse and Mental Health Services Administration, 2013); the rate of newborns with Neonatal Abstinence Syndrome increased from 1.20 to 3.39 per 1000 hospital births from 2000 to 2009 (Patrick et al., 2012); and in 2015, an HIV outbreak linked to injection of opioid pain relievers took place in Indiana. Insurance fraud is another source of health costs, especially among social healthcare programs. Costs to insurers exceed those from drug purchases as abusers utilize additional services such as doctor and hospital visits. A study analyzing Medicaid claims in search for indicators of potential inappropriate use or prescribing of opioids among enrollees found that 40% of recipients had at least one such indicator (Mack et al., 2015).

The crime costs associated with drug abuse arise from four main channels. The first is the pharmacological effect, as drugs may release inhibitions or increase aggression, thus leading to crime.[18] Second is the economic effect, as users may turn to crime to finance their addiction. Third is the systemic effect, where crime becomes a mean to resolve disputes as underground market participants cannot rely on contracts and courts (Goldstein, 1985; Miron, 1999; Corman and Mocan, 2000). The last channel is the drug abuse lifestyle, which may predispose criminal activity by offering opportunities to offend resulting from skills learned from other offenders. Evidence regarding the crime costs associated with prescription opioid abuse is

[18] In the context of opioid abuse, it is unlikely that the pharmacological channel plays an important role (Goldstein, 1985).

largely anecdotal. According to newspaper articles and reports by law enforcement agencies, these costs include medication theft, doctor shopping, insurance fraud, and other common criminal activity such as property and violent crime. The magnitude of these offenses, however, is unknown.

1.2 Controlled Substance Regulation and Enforcement

Prescription drugs are regulated under the 1970 Controlled Substances Act, and the Drug Enforcement Administration (DEA) serves as the primary federal agency responsible for its enforcement. The Act requires that any person who manufactures, distributes, dispenses, imports, or exports controlled substances must register with the DEA and keep records of inventories and transactions (Yeh, 2012).[19] Substances are classified into five schedules based on abuse potential, likelihood of dependence when abused, and whether they have accepted use in medical treatment.[20] While schedule I substances have no accepted use in medical treatment, schedules II-V include substances with recognized medical uses, and thus can be prescribed, administered, or dispensed. These tight regulations have given rise to an illegal market in which prescription drugs are diverted for abuse.[21]

To curb prescription drug abuse, the Office of National Drug Control Policy released the Prescription Drug Abuse Prevention Plan, which includes action in the areas of education, prescription drug monitoring (PDMPs), drug disposal, and enforcement.[22] While previous work has documented the impact of prescription drug

[19] Alcohol and tobacco are not considered controlled substances.

[20] The order of the schedule increases with less dangerous substances. Examples of substances in schedules I, II, III and IV are heroin, oxycodone, buprenorphine, and alprazolam, respectively.

[21] Prescription drugs are diverted through various channels that include doctor prescriptions, doctor-shopping, medication theft, and the Internet.

[22] Education intends to raise awareness among the public and healthcare providers. Monitoring through Prescription Drug Monitoring Programs, a statewide electronic database that collects data

abuse control strategies such as PDMPs, little is known about the effect of supply-side interventions such as enforcement.

Previous studies have focused on the effectiveness of enforcement on illegal drug markets. Theoretical work predicts that under enforced prohibition, the price of drugs will exceed that under legalization due to larger production costs from avoidance efforts, the expected value of confiscated drugs, and the expected costs of punishment (Becker et al., 2006). Marginal increases in enforcement raise a supplier's probability of conviction and thus, production costs. In turn, equilibrium prices should increase and quantities should decrease (except in the extreme case of perfectly inelastic demand). Empirical evidence regarding the impact of supply-side interventions is mixed. While prohibition seems to raise prices above those likely to pertain under legalization, most studies of the impact of marginal increases in supply-side enforcement find no effects, or at best, modest or temporary effects (See Pollack and Reuter (2014) for a discussion of this literature. DiNardo (1993); Weatherburn and Lind (1997); Yuan and Caulkins (1998); Miron (2003); Kuziemko and Levitt (2004); Dobkin and Nicosia (2009); Crane and A. Rivolo (1997); Dobkin et al. (2014); Cunningham and Liu (2003)). A notable exception is the Australian heroin drought in 2001, the most severe and lasting heroin shortage in the world. However, there is debate regarding whether this draught can be attributed to improved domestic drug enforcement (Wodak, 2008).[23] The existing evidence may not generalize to prescription drugs, which have accepted use in medical treatment, and thus, are

on dispensed substances, can help to identify "doctor shoppers." Drug disposal programs may help to limit the diversion of drugs, since many non-medical users obtain the drugs from family and friends. Finally, enforcement can help tackle prescribing outside the usual course of practice.

[23]National trends are also puzzling. Over the last decades of the twentieth century, drug enforcement, measured as federal budget and drug arrests, expanded dramatically. Meanwhile, purity-adjusted prices of cocaine and heroin more than halved (Basov et al., 2001; Boyum and Reuter, 2005).

legally produced and dispensed.

1.3 The Florida Pill Mill Crackdown

By the late 2000s, Florida had become the epicenter of America's prescription drug abuse epidemic and oxycodone was the drug in demand. Physicians operating from pain clinics, referred to as "pill mills," were the main source of drug diversion. Pill mill operations were known for the inappropriate prescribing and dispensing of controlled substances, nearly exclusive associations with specific pharmacies, cash-based payment methods, and casual examinations (Johnson et al., 2014). Pill mills proliferated in south and central Florida, serving not only state residents but also people from other states.[24] In mid-2010, law enforcement and legislative officials initiated a sweeping crackdown on Florida's pill mill suppliers. These included wholesale distributors, pain clinics, pharmacies, pharmacists, and physicians. There were two key aspects to this crackdown: enforcement and legislative action (see section 3.4 for alternative explanations).

Enforcement consisted of a series of investigations dubbed Operation Pill Nation that were led by the DEA in joint effort with state and local law enforcement authorities. These resulted in the surrender, suspension, revocation, or denial of the state medical license/ DEA Certificate of Registration of diverting healthcare providers, namely physicians, pharmacists, pain clinics, and pharmacies. Either temporarily or permanently, suppliers could no longer handle controlled substances. Another component of the strategy for Operation Pill Nation was to identify the distributors that were supplying controlled substances to diverting healthcare providers. In June 2010,

[24] According to pain clinic licensure data, Broward, Hillsborough, Miami-Dade, and Palm Beach counties accounted for approximately 45% of all Florida pill mills. These counties also contained most of the top oxycodone dispensing doctors in the U.S.

the DEA took administrative action against four such wholesale distributors (DOJ, 2011; DEA, 2011d). Aggressive enforcement efforts continued throughout 2011 and 2012.[25]

Legislative action (bills SB 2272 and HB 7095) targeted pain clinic suppliers in a variety of ways, but most notably by amending Dispensing Practitioner Laws (Florida Statute 465.0276).[26] The amendment was first enacted in June 2010 and became effective in October of 2010. Additional elements became effective in July, 2011. Before these changes, authorized Florida practitioners were allowed to prescribe and dispense controlled substances in schedules II-V. SB 2272 amended the law by dictating that practitioners working from pain clinics could only dispense up

[25]Examples of notable enforcement efforts included: (1) multiple crackdowns on pain clinics, the largest two of which took place in South Florida on February, 2011 and Central Florida on October, 2011. These two operations resulted in 118 arrests, the surrender of more than 80 DEA registrations, and the seizure of more than $19 million in assets (DEA, 2011b; DOJ, 2011; DEA, 2011d, 2013). Crackdowns on pain clinics continued into 2012 (DEA, 2012d); (2) administrative action against large distributors. To name a few examples, *Harvard Drug Group, LLC* received an Immediate Suspension Order in June, 2010 for distributing over 13 million dosage units of oxycodone products to Florida pharmacies between March 2008-2010 (DEA, 2010, 2011c); *KeySource Medical, Inc.* received an Immediate Suspension Order in June, 2011 for distributing 48 million dosage units of oxycodone products to customers in Florida between November 2008-2010. Moreover, between 2009-2011, KMI sent over 52 million dosage units of oxycodone into Florida, including over 44 million units in 2010 alone (DEA, 2011a; DOJ, 2012); *Cardinal Health* received an Immediate Suspension Order in February, 2012 (DEA, 2013). In three years, Cardinal's Lakeland center supplied more than 12 million dosage units of oxycodone to four pharmacies in Florida (DEA, 2012c); and *Walgreens Distribution Center in Jupiter* received an Immediate Suspension Order in September 2012 for distributing over 15 million dosage units of oxycodone between 2009-2011 to six of the top ten oxycodone purchasing pharmacies in the nation, all of which were in Florida (DEA, 2012b); (3) administrative action against multiple pharmacies, including chain stores such as CVS and Walgreens (DEA, 2013, 2012b,a); and finally (4) administrative action against dozens of doctors, many of which resulted in arrests.

[26]Other notable feature of these laws included requiring pain clinics to register with the Florida Department of Health. Note, however, that any physician operating in these clinics, and in Florida more generally, was already required to be registered with the DOH and the DEA. Additionally, pain clinics were banned from advertising that they sold narcotics and were required to be owned by physicians.

to a 72-hour supply of controlled substances in schedules II-V to a patient paying in cash, check, or credit card.[27] In July 2011, HB 7095 expanded upon these efforts by stating that practitioners could not dispense substances in schedules II & III.

Whether through enforcement or legislative action, the aim of the pill mill crackdown was the same: to disrupt diverting legal suppliers' ability to dispense or prescribe controlled substances. The intervention resulted in a massive shutdown of Florida's pain clinics. From 988 active pain clinic licenses in June 2010, only 376 were still active in June 2013 (see Figures 1 and 2). These closures, alike the crackdown, occurred throughout 2010-12 and not all resulted from incapacitation. Licensure data shows that many licenses were relinquished, suggesting that deterrance played an important role. A massive decline in prescription drug supply in the state followed.

Figure 3 plots potency adjusted grams per capita by drug group.[28] Figure 4 slices the data even further by plotting oxycodone and prescription substitutes by active ingredient. During the early 2000's, the evolution of Florida's oxycodone supply mirrored that in the rest of the country. In 2006, Florida's oxycodone supply rose at a faster pace while that of prescription substitutes slowed down, suggesting there was substitution towards oxycodone.[29] Between 2007-10, Florida's oxycodone supply rose even faster, surpassing the slowdown in prescription drug substitutes. It is unclear to what extent this exponential growth is attributable to increases in total users or increases in total supply per user. Specifically, while the trend might be

[27]The law excluded practitioners dispensing to workers compensation patients or insured patients paying a copay or deductible in cash, check, credit card.

[28]Note that stimulants are not potency adjusted as these are not opioid drugs.

[29]An outlier value in the fourth quarter of 2007 can be observed across all controlled substances in the state of Florida. It is unclear whether this figure represents a true amount or is the result of error. This outlier is observed across all of ARCOS datasets, but it is not observed in consumption data such as hospitalizations or drug deaths.

explained by exponential growth in the number of users, it might also be explained by addiction. Addiction is characterized reinforcement, tolerance, and withdrawal (Cawley and Ruhm, 2011).[30] These properties imply that with continued prescription drug consumption, larger quantities will be necessary to maintain a certain level of utility. In the absence of constraints, the consumption path of users should increase progressively even when the number of users stays fixed.

In mid-2010, Florida's oxycodone supply faced an abrupt drop, followed by a steady decline that reached national levels in 2013. Meanwhile, oxycodone supply continued to increase in the rest of the U.S. but at a slower pace. There is no evidence of an oxycodone supply recovery or of substantial substitution to other opioid pain relievers within the state. Figure 5 plots total oxycodone grams by state to examine for the presence of oxycodone spillovers across states –say, if a 10 gram decrease in Florida resulted in a 10 gram increase in Georgia.–[31] There is no evidence of substantial spillovers.[32]

The weak regulatory environment in Florida, the crackdown on internet pharmacies, and the introduction of Medicare Part D likely triggered this epidemic in the state. Florida has one of the highest rates of Medicare beneficiaries in the nation. The introduction of Part D might have led to the proliferation of pain clinics, an increase in the number of prescription drugs prescribed, and the advertisement of prescription drugs. Previous work by Pacula et al. (2015) found that opioid distribution increased faster in states with a larger fraction of Part D beneficiaries. Also, work by Alpert et al. (2015) found that Part D led to large relative increases in direct-to-consumer advertising in geographic areas with a high concentration of

[30]Reinforcement implies that $U_{cs} > 0$, tolerance that $U_s < 0$, and withdrawal that $U_c > 0$, for utility function U, stock of past consumption s, and current consumption c.

[31]Absolute grams are plotted to detect the magnitude of these spillovers.

[32]See Section A.3 in the Appendix for more details.

Medicare beneficiaries. As for internet pharmacies, in fiscal year 2007, the DEA issued Immediate Suspension Orders against 10 pharmacies operating from Florida. Reportedly, these pharmacies diverted millions of dosage units of hydrocodone across the U.S. through the internet (NDTA, 2009). This might have also led to the entry of pain clinics.

2 Empirical Approach

2.1 Data Sources

The outcomes of interest include prescription drug quantities, street prices, number of suppliers, deaths, inpatient and emergency department hospital discharges, pain clinic licenses, index crimes, drug arrests, drug theft, and substance abuse treatment admissions. Outcomes are drawn from fourteen datasets collected by novel administrative and online sources.

Drug street price data are drawn and pooled from two websites, StreetRx and Bluelight, both of which rely on crowdsourcing. StreetRx is operated by Epidemico, a public health software and data analytics company under contract from the RADARS System. Bluelight is operated by volunteers and includes in its message board a series of annual price threads where members of the community post drug street prices in their city.[33] StreetRx is available from 2010-2013, while Bluelight.org is available from 2008-2010. Variables include drug name, date of post, price, mg strength, formulation, city, and state. Date of post is used as a proxy for date of purchase. A weakness worth noting is that these prices might not be representative of all street

[33]Since the information is contained in messages rather than in a usable format, a dataset is constructed by reading each post, and selecting those that identify Florida.

prices because only abusers who participate on such websites report. Also, for some drug-quarters there are few or no observations.

Quantities, measured in grams, are drawn from DEA's Automation of Reports and Consolidated Orders System (ARCOS), a drug reporting system that monitors the flow of controlled substances from their point of manufacture through commercial distribution channels to point of sale or distribution at the dispensing/retail level. ARCOS' Reports 2 and 5 are used in this study, both of which provide total grams purchased by hospitals, pharmacies, practitioners, mid-level practitioners, narcotic treatment programs, and teaching institutions. Both reports cover sales by state, by active ingredient (for substances in schedules I & II and selected substances in schedule III), and are available from 2000-13. The main distinction between these sources is that Report 2 identifies total sales at the year-quarter level, while Report 5 identifies total sales at the year level, with totals broken by provider type. Suppliers data are also drawn from ARCOS' Report 5. This outcome captures the total number of providers that were purchasing controlled prescription drugs by active ingredient, state, and provider type. Data for morphine, hydromorphone, and fentanyl are not reported in 2012. To circumvent this issue, missing values are imputed using ARCOS dosage units data which was reported in 2012, and average grams per dosage unit in 2011 and 2013.[34] As for total buyers, missing values are imputed using the average value in 2011 and 2013.[35] Two outliers are dropped and inputed with the average value in the previous and following date. Specifically, South Dakota and South Carolina display a dramatic one time jump in fentanyl grams in the second quarter of 2011 and in the first quarter of 2013, respectively. While it is unclear whether or not these observations represent real values, they are unlikely related to the Florida

[34] $imputedgrams_{2012} = dosageunits_{2012} mean(grams/dosageunits)_{2011,13}$

[35] $imputedbuyers_{2012} = mean(buyers)_{2011,13}$

context.

Drug related deaths are drawn from toxicology reports submitted to the Florida Medical Examiners Commission. This data reports drugs found in deceased persons for 50 monitored drugs and identifies if the drug was merely "present" in the body or if it was the "cause" of death. I focus on deaths where the drug played a causal role as to capture prescription drug abuse rather than legal consumption. Individual-level data identify county, month, and active ingredient. Although data are available from 2007 to 2013, counties are identified starting in 2009.

Inpatient and outpatient emergency department hospital discharges are drawn from the Florida Agency for Healthcare Administration. Discharge-level data are available from 2008-12, and identify county and quarter. The variables "admitting diagnosis" and "principal diagnosis" are used to identify admissions primarily caused by drug abuse. Selected individuals include those with the following ICD-9-CM codes: 304 Drug dependence; 305 Nondependent abuse of drugs; 292 Drug-induced mental disorders (includes withdrawal); and 960-979 Poisoning by drugs (includes overdose). Conditional on admission for these diagnoses, drug class is identified using "admitting diagnosis," "principal diagnosis," "other diagnosis," and "external cause of injury."[36] The ICD-9-CM codes are: Opioids 304.0, 304.7, 305.5, 965.0, E850.0, E850.1, E850.2, E935.0, E935.1, and E935.2; Benzodiazepines –complements– 304.1, 305.4, 969.4, E853.2, and E939.4; Amphetamines 304.4, 305.7, 969.72, E854.2, and E939.7; Cannabis 304.3, 305.2, 969.6, E854.1, and E939.6; Cocaine 304.2, 305.6, 970.81, E855.2, and E938.5; and Heroin 965.01, E850.0, and E935.0. Facilities specializing in rehabilitation are dropped from the inpatient file as these enter the data in 2010.

[36]Unlike other outcomes, these datasets identify drug class rather than active ingredient, making it impossible to report estimates for the previously established drug groups.

Pain clinic licensure data are drawn from Florida's Department of Health. Firm-level data reports the date a license was first granted, revoked, or relinquished, practice name, and practice location address. Data are available from late 2009 to 2013. Dates are used to proxy market entry and exit. Location addresses are geocoded and spatially linked to U.S. Census Cartographic Boundary files for Florida using Geographical Information Systems.

Index crime data are drawn from the Florida Department of Law Enforcement's (FDLE) Uniform Crime Reports (UCR) Program. UCR numbers reflect the crimes reported by the local agencies (e.g. Sheriff Offices and Police Departments) to FDLE. This system provides standardized reports on property and violent crime as well as drug arrest statistics by year and county. Nation-level UCR data on property crimes, violent crimes, and drug arrests is also used. This data are drawn from the Federal Bureau of Investigation (FBI) and are available by year and state. FDLE and FBI datasets are available up to 2013. Armed Robbery and Night Break-In counts are drawn from the Drug Theft or Loss data collection system, in which registrants report their controlled substance losses to the DEA. This data are available from 2009-2013, by year, county, and state.

Substance abuse treatment admissions data are drawn from the Treatment Episode Data Set - Admissions (TEDS-A). TEDS-A provides annual information on the number and characteristics of persons 12 or older admitted to public and private substance abuse treatment programs that receive public funding. Admission-level data are collected annually up to 2012 and identify state, patient characteristics, and up to three abused substances. Admissions where the primary substance is alcohol or not disclosed are dropped. DC, Georgia, and Mississippi are dropped because they don't report to TEDS-A during most periods of interest.

2.2 Econometric Strategy

The empirical strategy is to compare changes in outcomes in areas that were most affected by the epidemic to those in areas that were less affected. Naturally, epidemic intensity is not randomly assigned as affected areas might differ in level or growth of socio-economic status, population characteristics, and healthcare utilization. Therefore, the strategy is to test for level or trend breaks in pre-existing differences in outcomes after the crackdown in mid-2010. The identifying assumption is that absent the intervention, pre-period differences would have continued on the same trends.

The general econometric specifications are depicted below. Equation 1 is a linear spline specification that estimates the slope and intercept deviations between treatment and control groups, before and after the intervention. Equation 2 is a difference-in-differences specification that estimates the overall effect of the intervention. All outcomes of interest Y_{gy} are in logs as these are based on count data and reflect variation in the size of the unit of observation. To avoid the loss of observations with a count of zero, 1 is added to all outcomes. All datasets are balanced. The treatment group $Treat_g$, post-period $Post_y$, time trend t_y, and outcomes of interest Y_{gy} are indexed by geographic unit g and period y. For consistency across datasets and due to the imposition of a linear trend, the sample is restricted to the years 2008-12. Standard errors are clustered at the geographic unit level.

$$\begin{aligned} ln(Y_{gy}) = \alpha_0 + \alpha_1 Treat_g + \alpha_2 Post_y + \alpha_3 Post_y Treat_g + \alpha_4 t_y \\ + \alpha_5 t_y Treat_g + \alpha_6 t_y Post_y + \alpha_7 t_y Post_y Treat_g + \epsilon_{gy} \end{aligned} \tag{1}$$

$$ln(Y_{gy}) = \beta_0 + \beta_1 Treat_g + \beta_2 Post_y + \beta_3 Post_y Treat_g + \epsilon_{gy} \tag{2}$$

Data limitations condition the choice of counterfactual as some outcomes are available for all U.S. states, while others are only available for the state of Florida. When data are available for all states, outcomes in Florida are compared to outcomes in other states. In this case $Treat_g$ is a dummy variable equal to one for Florida and zero otherwise, $Post_y$ is a dummy variable equal to one in the post-period and zero otherwise, and t_y is a linear time trend (e.g. ...,-2,-1,0,1,2,...). In Equation 1, α_3 and α_7 indicate the differential intercept and slope effect experienced by the treatment group after the intervention. In Equation 2, β_3 indicates the overall effect experienced by the treatment group after the intervention.[37] Although one might be concerned that spillovers threaten the validity of cross-state estimates, Figure 5 does not support this theory.[38]

The usual asymptotic approximations assume that both, the number of treatment and control groups is large. However, in this setting only one state is treated and thus, statistical inference requires an alternative approach. To that end, a variant of Fisher's permutation test is implemented (see Buchmueller et al. (2011); Cunningham and Shah (2014)). For this test, Equations 1 and 2 are estimated 50 additional times, each time assigning the $Treat_g$ dummy to a different state or to the District of Columbia. P-values are constructed using the placebo distribution to test the hypothesis that Florida's effect is different from zero. The 5th and 95th percentiles of the distribution of placebo estimates –excluding Florida–, Florida's rank among the total number of states, and the total number of states –including Florida– are reported. With 50 placebo estimates, achieving 10% and 5% significance in a two-sided test requires that Florida's coefficient is ranked second (p-value=.08) and first

[37] Coefficients are given the difference-in-semielasticities interpretation $100 \times (e^{((Post)+(Treat \times Post))} - e^{(Post)})$ proposed in Shang, Nessony and Fanz (2016).

[38] Spillovers might occur if the intervention induced users to seek oxycodone elsewhere. See Section A.3 in the appendix for more details.

(p-value=.04) from the top or bottom of the placebo distribution, respectively. Since this approach yields conservative confidence bounds, the 10% level is emphasized.

As a robustness check of β_3, outcomes in Florida are also compared to outcomes in "synthetic" Florida. Synthetic Florida is constructed following the synthetic control methods described in Abadie et al. (2010). The approach to inference is similar to the permutation test. Specifically, a placebo distribution is constructed by applying the synthetic control method to all other 49 states and DC. This methodology may not always succeed at finding an appropriate counterfactual as there may not be a convex combination of "control" states that can reproduce the pre-intervention time series in the "treatment" state. Because states with a poor fit do not provide reliable information about the relative rarity of Florida's intervention, inference is also conducted by excluding states with a pre-intervention mean squared prediction error above the 90th percentile.

When data are only available for Florida, outcomes in pill mill counties are compared to outcomes in the rest of the state. $Treat_g$ is a continuous variable that measures the total pain clinics per 1,000 population in a county pre-intervention (see Figure 1). The geographic location of supply might not map that of demand as Floridians from all counties likely traveled to the pain clinics. This implies that Floridians as a whole would be affected by the epidemic and interventions. Nonetheless, transaction costs from traveling and searching should be lower for pain clinic county residents, making their optimal pre-period consumption higher.[39] Thus, cross-county estimates $\beta_3, \alpha_3, \alpha_7$ can be interpreted as the heterogenous treatment effect for pill mill counties. This analysis provides further evidence of the link between

[39]This is especially true as prescriptions for controlled substances in schedule II cannot be refilled, and although practitioners can issue multiple prescriptions, the combined effect of these cannot exceed a 90-day supply.

changes in outcomes and the pill mill crackdown by showing that those who should have been most affected indeed were.

Estimates are classified into groups based on active ingredients and their relation to oxycodone. These include oxycodone, prescription drug substitutes, illegal drug substitutes, prescription drug complements, opioid abuse treatment (OAT) drugs, other illicit drugs, and amphetamines (see Table 7 in the Appendix). Prescription drug substitutes include other schedule II or III opioids not used in opioid abuse treatment. Illegal drug substitutes include other schedule I opioids. OATs include other schedule II or III opioid pain relievers used in opioid abuse treatment. Prescription drug complements include schedule IV benzodiazepines that tend to be abused with opioid pain relievers.[40] Amphetamines are schedule II and highly abused prescription drug stimulants that are not associated with the painkiller epidemic.

3 Results

3.1 Drug Availability

This section analyzes the impact of supply-side interventions on prescription drug availability as measured by quantities and street prices. Either through a supply shortage or a price increase, a successful intervention should reduce oxycodone quantities. The effect on overall opioid pain reliever supply is unclear a priori as it depends, among other things, on whether substitute drugs were directly or indirectly affected by the crackdown.[41] If directly affected, the supply of other opioid pain

[40] Benzodiazepines are also abused on their own.

[41] Amendments to dispensing practitioner laws targeted controlled substances in schedules II & III. As for enforcement, when a DEA registration is revoked, the supplier can no longer handle any controlled substances. Nonetheless, if deviant doctors were primarily diverting oxycodone, then the crackdown will have a small effect on other opioids.

relievers should decrease, but if not directly affected, the supply could even increase if oxycodone's shock generates an upward demand shift towards these drugs.

3.1.1 Prescription Drug Quantities

Table 1 reports estimates from Equation 1, where $Treat_g$ is a dummy variable equal to one for Florida. This specification allows Florida's trend to be differentially affected by the crackdown and adjusts for nation-level interventions that might have occurred during the post-period.

Pre-crackdown, the growth rate of quarterly oxycodone supply in Florida was approximately six percentage points higher than that in the rest of the country. Post-crackdown, the growth rate of quarterly oxycodone supply in Florida was approximately eighteen percentage points lower than that of the control group. Most coefficients are significant at the 1% level when state clustered standard errors are used. However, when the placebo distribution is used, only oxycodone's coefficients are significant at the 5-10% level. Between 2010-12, average oxycodone and substitute supply in Florida was 59% lower and 3% higher than what it would have been in the absence of the crackdown. When re-calculating the percentage change in average oxycodone supply, but assuming that in the absence of the crackdown Florida would have continued on its pre-trends, the reduction is 62%.

The percentage change in average supply at different points in time is also depicted in the table. The decline in oxycodone supply, like the crackdown and pain clinic closures, was gradual. This gradual decline need not result in gradual changes in other outcomes due to the addictive property of prescription drugs. Pre-crackdown, utility among non-medical users might have remained constant as total grams increased exponentially. Post-crackdown, however, utility levels likely

declined, generating a number of behavioral responses depending on the level of the stock of past consumption.

3.1.2 Prescription Drug Street Prices

The previous section documented a substantial decline in prescription drug quantities. If this decline is the result of a shock to supply, then it should be accompanied by an increase in prices. This section explores the effect of supply-side interventions on prescription drug street prices. In 2013, 4.3% of past-year non-medical users aged 12 or older reported that drug dealers were their source of opioid pain relievers (Substance Abuse and Mental Health Services Administration, 2014), suggesting that the street market is small. Thus, street prices may not be representative of the average prices paid by non-medical users neither reflect the prices paid to physicians or pharmacies. Nonetheless, street prices may reflect a shortage in the legal market if healthcare providers were drug dealers' source of prescription drugs.

Figure 6 plots street prices per milligram for oxycodone, complements, and substitutes. Data for prescription substitute drugs includes hydrocodone prices only because there are not enough observations for other drugs. Pre-crackdown, oxycodone, complement, and substitute street prices were stable. Post-intervention, street prices spiked by 238%, 114%, and 140%, respectively (see Table 2). This provides further evidence that supply, rather than demand-side interventions, can explain the decrease in quantities.

At a first glance, results might seem conflicting with economic theory which would not predict a price increase for oxycodone's complements. Note that alprazolam was being dispensed and prescribed from the pill mills, and although its supply would not be directly affected by the dispensing laws, it would be directly affected

by enforcement. These findings suggest that enforcement was effective at reducing street availability. As for substitutes, note that total hydrocodone supply declined during the post-period (see Figure 4), which can explain the price increase. Moreover, physician dispensing decreased sharply across all prescription drugs in mid-2010.[42] If dispensing physicians were drug dealers' source of opioid pain relievers, then street prices should increase across all prescription drugs.

3.2 Drug Abuse and Public Health

This section analyzes the effect of supply-side interventions on prescription drug abuse and health as measured by deaths, hospitalizations, and substance abuse treatment admissions. Previous sections found a substantial decline in Florida's oxycodone supply and no substantial oxycodone or prescription substitute spillovers across states. If non-medical users manage to find these drugs through illegal suppliers, opioid pain reliever consumption might not match legal supply. However, if legal suppliers rather than illegal ones are the original source of most diverted prescription drugs, then Florida's oxycodone consumption should decline. More generally, one would expect changes in prescription drug supply to translate into similar changes in consumption. The effect on illegal drug substitutes is yet to be explored. Since illegal drugs were not targeted, a negative shock to oxycodone supply should result in a positive shock in the demand of illegal drug substitutes.

3.2.1 Deaths

Figure 7 plots total instances in which a drug played a casual role in a person's death. Declines in oxycodone quantities were followed by substantial declines in

[42] See Figure 14 in Appendix for graphic evidence.

deaths. Complement drugs also displayed substantial declines in deaths. Prescription substitutes continued on their pre-intervention trends. It is worth noting there is heterogeneity in the post-intervention response of different drugs within this group. Specifically, morphine and hydromorphone deaths increased, suggesting there was substitution toward other opioid pain relievers.[43] One possible explanation is that doctors, either due to deterrence or unavailability of other opioids, switched to these drugs. Deaths by heroin, an illegal drug substitute, also increased post-intervention. The offsetting effect from increases in heroin, morphine, and hydromorphone deaths was small relative to the substantial gains from decreases in oxycodone deaths.

Table 7 reports results from Equation 1, where $Treat_g$ is a continuous variable that represents the total pain clinics per 1,000 population in the county pre-crackdown. During the epidemic, oxycodone and complement deaths increased faster in pill mill counties. Post-intervention, oxycodone and complement deaths decreased while heroin deaths increased faster in pill mill counties. Deaths from other illicit drugs are statistically insignificant. Estimates can be interpreted more meaningfully by considering pill mills per 1,000 population in a given county. Take for instance Broward county, a main hot spot for drug diversion at the time, with .0761 pill mills per 1,000 population. Prior to the intervention, the growth rate of quarterly oxycodone deaths in Broward county was 10%.[44]

3.2.2 Hospital Discharges

Table 4 reports estimates from Equation 1, where $Treat_g$ is a continuous variable that represents the total pain clinics per 1,000 population in a county pre-crackdown.

[43] These findings coincide with those from ARCOS Report 2 (see Figure 4) which also display post-intervention increases in the supply of these drugs.

[44] $(100 \times [(0.00) + (1.26) \times .0761 = .0958])$

Due to data limitations, estimates are reported by drug class (e.g. all opioids, all benzodiazepines, etc.) rather than drug group (e.g. oxycodone, OAT, prescription substitutes, etc.). Results are consistent with those found for deaths. Panel A shows that before the crackdown, inpatient hospitalizations with a mention of opioid misuse increased faster in pill mill counties. Post-crackdown, opioid and complement hospitalizations decreased while heroin hospitalizations increased more in pill mill counties. Other drug classes are statistically insignificant. Similar results are found for outpatient emergency department discharges (See Panel B).

3.2.3 Substance Abuse Treatment

Florida experienced a substantial decline in prescription drug supply. In response, users either switched to substitute drugs or ceased consumption. Because drugs are addictive, users often rely on substance abuse treatment to help cease consumption. This section examines the impact of supply-side interventions on substance abuse treatment (see Figure 8 and Table 5).[45]

Table 5 report results from Equation 2 and the synthetic control method using TEDS-A data, which measures annual admissions to substance abuse treatment facilities receiving public funding.[46] Estimates are available by drug class rather than drug group. Panels A and B include admissions in which the given substance is reported as a drug problem and thus, will reflect co-abuse. Panel C includes admissions in which the given substance is reported as the primary drug problem. Post crackdown, the average number of admissions with a mention of opioids and complements

[45] See appendix for graphical evidence on parallel trends.

[46] One concern is that the number of facilities receiving public funding might have increased after the crackdown. To assess for the possibility of an increase in survey participants rather than in admissions, Figure 8 and Table 5 display outcomes for illegal drugs that were considered the primary problem. Admissions in which opioids are the primary substance are driving the results.

increased by 33% and 42%, suggesting that many individuals sought to rehabilitate.

3.3 Crime and Punishment

This section explores the effect of supply-side interventions on crime and punishment. A priori, it is unclear whether a crackdown on legal suppliers will increase or decrease crime. Recall that drug abuse is linked to criminal activity through four main channels: systemic, economic, lifestyle, and pharmacologic. A reduction in equilibrium quantities need not result in less crime as depending on the elasticity of demand, total expenditures in the production and consumption of these drugs can increase and thus, economic oriented crime.[47] Criminal activity might also increase if drug theft, rather than consensual doctor-user transactions, becomes the prefered way to divert prescription drugs. Finally, a crackdown on legal suppliers may affect crime through its impact on illegal drug markets as the demand for substitute illegal drugs can increase. A larger illegal drug market may increase commercial disputes and therefore systemic oriented criminal activity.

To assess this question empirically, I examine drug arrests, property crimes, violent crimes, and drug theft (see Table 6). Drug theft measures total controlled substance losses reported by suppliers to the DEA due to armed robbery or night break-in. In Panel A, the treatment group is Florida and the control group is all other states.[48] In Panel B, the treatment group is Florida and the control group is synthetic Florida. In Panel C the treatment group is a continuous variable defined as the total number of pain clinics per 1,000 population in the county pre-intervention (see Figure 9).

[47]Specifically, for elastic demand total expenditures in drug production and consumption will decrease, while for inelastic demand total expenditures will increase.

[48]See appendix for graphical evidence on parallel trends.

With the exception of drug arrests, estimates in Panel A closely resemble those in Panel B, suggesting that the coefficients are robust to the choice of counterfactual. There is no compelling evidence that supply-side interventions had an effect on index crimes or drug arrests. This is consistent with the conviction of a small number of big suppliers rather than the conviction of a large number of small suppliers or individual consumers, and suggests small social costs of punishment from incarceration. As for drug theft, Panel A shows that post-crackdown such reports declined by 40%. Pill mill counties are driving these results.

3.4 Alternative Explanations

Two other interventions taking place during Florida's crackdown may raise concerns regarding the interpretation of the findings. These were the implementation of Florida's PDMP and the introduction of OxyContin's abuse-deterrent formulation. In this section, I discuss each intervention and argue why it is unlikely these represent a significant source of bias, starting with the fact that neither could plausibly explain the "disappearance" of suppliers (Figures 2 and 14).

3.4.1 OxyContin Re-formulation

OxyContin is the oxycodone brand name produced by Purdue Pharma. In August 2010, an abuse-deterrent formulation of extended-release OxyContin entered the market, while shipments of the original formulation ceased. The new tablet could not be easily broken, chewed, or dissolved. This intervention is unlikely to be an important source of bias. First, abusers could still ingest the pill and experience its potent high or switch to non-reformulated oxycodone tablets.[49] Second, Hwang

[49]Purdue Pharma is one in many producers of oxycodone. Even if many users to ceased OxyContin consumption, nearly perfect substitutes were still available, namely, generics and other brand

et al. (2015) show that OxyContin sales nationwide were unaffected –and at most, only slightly negatively affected– after the re-formulation. Third, this intervention should have affected oxycodone supply in all states, not only in Florida. Figures 5 and 4 show no evidence of a decline for other states, let alone, a substantial decline as that in Florida. Fourth, the re-formulation cannot explain declines in other opioids or in benzodiazepines among users that did not co-abuse.[50] Additionally, it cannot explain declines in non-reformulated oxycodone tablets. Figure 10 plots oxycodone grams for OxyContin and non-reformulated oxycodone using Drug Utilization Reports for the Florida Medicaid Program. While not a representative sample, the data clearly shows that the supply of non-reformulated tablets declined sharply. Finally, the re-formulation should have resulted in a downward shift of the demand curve, leading to a decrease in prices. Figure 6 suggests otherwise.

3.4.2 Florida's Prescription Drug Monitoring Program

PDMPs are electronic databases that track substances dispensed in a state and aim to address the problem of asymmetric information arising when practitioners cannot differentiate medical from non-medical users. The information collected is available to registered healthcare providers to help guide their prescribing decisions.[51] Florida's PDMP became operational in September 2011, and practitioners began accessing the data in October 2011.

Several sources have attributed the decline in oxycodone deaths to the implementation of Florida's PDMP. Yet, the evidence strongly suggests that the PDMP

names such as Percocet and Roxicodone.

[50]While prescription substitutes continued on their pre-intervention trends, there is heterogeneity in the post-intervention response among drugs within this group.

[51]The data collected usually includes the names and contact information for the patient, prescriber, and dispenser; the name and dosage of the drug; the quantity supplied, the number of authorized refills; and the method of payment.

is not an important source of bias. First, it became operational and accessible well over a year after oxycodone's sharp trend break in mid-2010. Figure 11 plots total oxycodone grams in Florida using ARCOS data. ARCOS measures healthcare provider purchases for future retail sale and unlike deaths or hospitalizations, can capture the timing of the crackdown without reflecting patient inventories. Second, the 2011-2012 PDMP Annual Report suggests that the database was not being used substantially. From October 2011 to September 2012, the PDMP received 2.4 million queries by registered users, far below the 44.5 million prescription records reported to the PDMP. This is not surprising as providers were not required to check the database and law enforcement was not allowed direct access.[52] Third, it is unlikely that prescription drug diversion in Florida resulted from asymmetric information.[53] Fourth, previous PDMP studies report small or no impact of implementation on supply (Brady et al., 2014, Paulozzi et al., 2011). A study examining the impact of the PDMP in Florida near the date of implementation only finds slight declines in opioid prescribing and use (Rutkow et al, 2015).[54] I address this threat more rigorously by exploiting ARCOS data and the timing a PDMP became operational (providers start reporting to the database) and accessible (providers start searching the database) in states other than Florida (see Figures 13 and 12). I find no effect of implementation on prescription drug supply. See Section A.5 in the appendix for the full analysis.

[52]Florida allows indirect access via a report in response to a request from law enforcement as a part of an active investigation.

[53]Florida physicians dispensed 94% of all physician dispensed oxycodone in the nation and operated at large-scale from pill mills. Pill mill counties are driving my results.

[54]Note that these findings will be confounded with the pill mill crackdown in Florida which began prior to PDMP implementation.

4 Conclusions

The social costs of supply-side interventions are substantial; yet, multiple studies fail to find evidence that marginal increases in enforcement sustainably and substantially raise prices and reduce consumption in the market for illegal drugs. This study suggests that at least in the medium-run, targeting the legal suppliers of pharmaceuticals can be an effective policy tool in the war against prescription drug abuse, especially in the face of an epidemic.

While drug epidemics are rather common and far-reaching events, future research should study the effectiveness of prescription drug supply-side interventions in non-epidemic settings. Future research should also study the effect of supply-side interventions on medical patients, as their access to treatment might be hindered by a shock to healthcare providers.[55]

[55]Due to data limitations, this issue is not addressed on this paper.

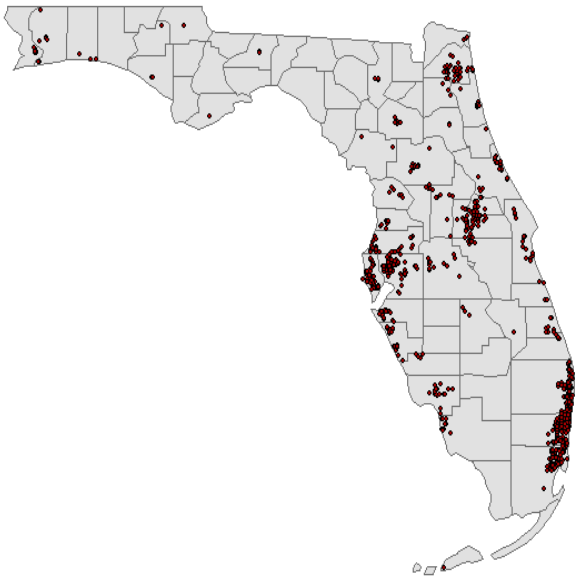


Figure 1: Pain Clinic Licenses in June 2010

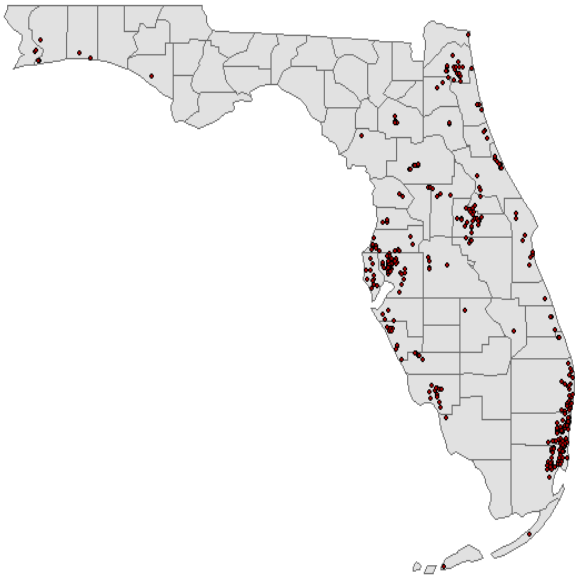


Figure 2: Pain Clinic Licenses in June 2013

Notes: Figures 1 and 2 are constructed using licensure data collected by Florida's Department of Health (see Section 2.1 for details). Location addresses are geocoded and spatially linked to U.S. Census Cartographic Boundary files for Florida using ArcGIS.

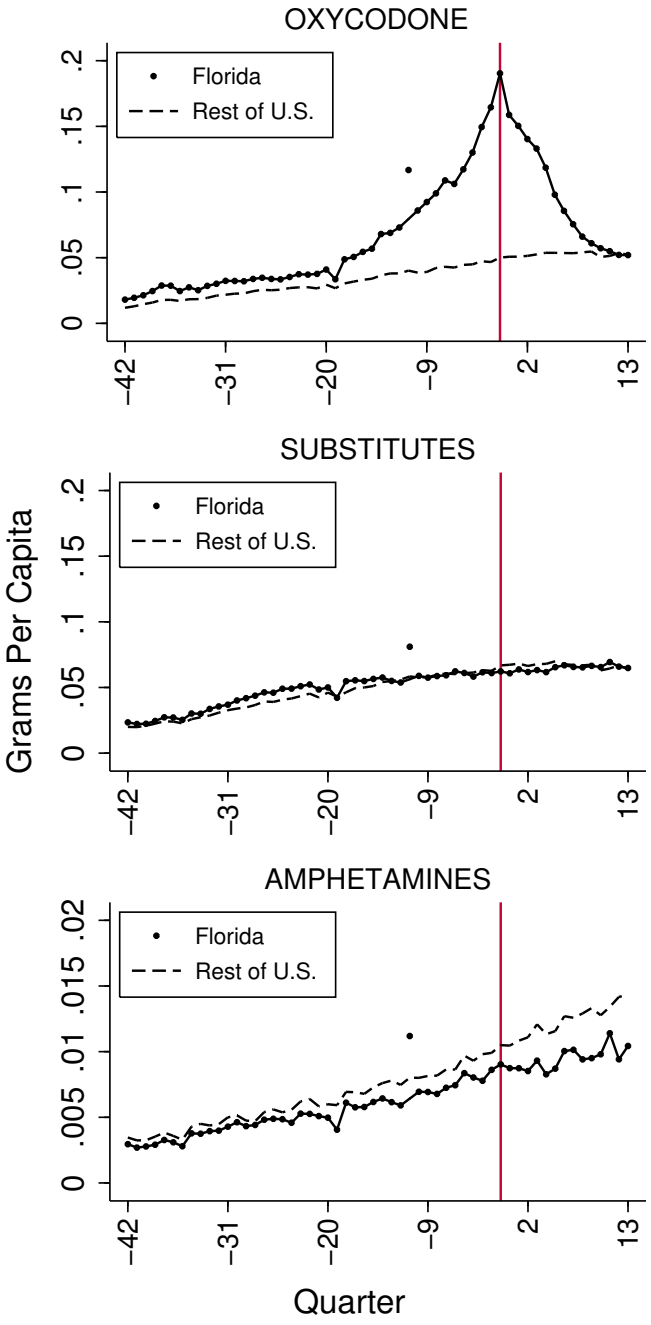


Figure 3: Prescription Drug Supply 2000-2013

Notes: Figure is constructed using ARCOS Report 2 (see Section 2.1 for details). Grams are divided by 2010 population estimates and adjusted for potency as described in the appendix. See appendix (Table 7) for the active ingredients in each drug group.

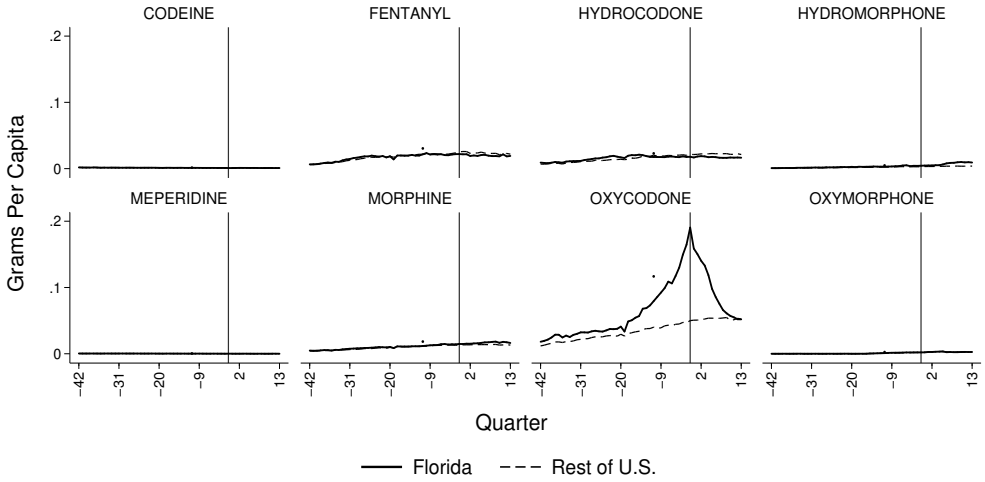


Figure 4: Opioid Supply Per Capita by Active Ingredient 2000-2013

Notes: Figure is constructed using ARCOS Report 2 (see Section 2.1 for details). Grams are divided by 2010 population estimates and adjusted for potency as described in the appendix.

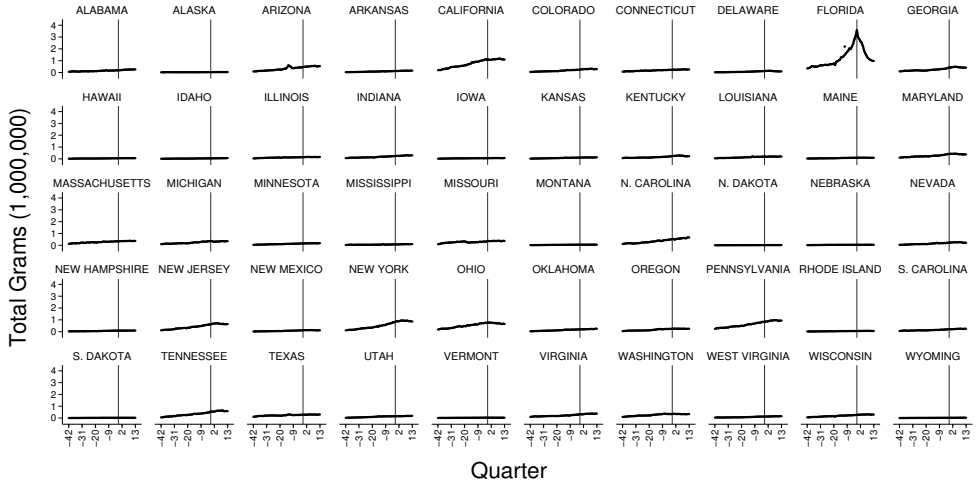


Figure 5: Oxycodone Supply by State 2000-2013

Notes: Figure is constructed using ARCOS Report 2 (see Section 2.1 for details).

Table 1: Log Prescription Drug Grams 2008-2012

	Oxycodone	Substitutes	OATs	Ampheta.
$Florida \times t$	0.059	-0.006	-0.014	0.000
	(0.002)***	(0.001)***	(0.002)***	(0.001)
$Rank/Total$	51/51	12/51	10/51	27/51
$[p5, p95]$	[-0.02, 0.02]	[-0.02, 0.01]	[-0.02, 0.02]	[-0.01, 0.01]
$Florida \times t \times Post$	-0.185	0.017	-0.011	-0.011
	(0.003)***	(0.002)***	(0.002)***	(0.002)***
$Rank/Total$	1/51	47/51	12/51	7/51
$[p5, p95]$	[-0.03, 0.03]	[-0.02, 0.03]	[-0.02, 0.03]	[-0.02, 0.01]
$Florida \times Post$	-0.103	-0.045	0.063	-0.047
	(0.008)***	(0.007)***	(0.010)***	(0.007)***
$Rank/Total$	2/51	8/51	45/51	9/51
$[p5, p95]$	[-0.09, 0.11]	[-0.12, 0.06]	[-0.13, 0.09]	[-0.10, 0.07]
R^2	.99	.99	.99	.99
N	1,020	1,020	1,020	1,020
$Level\ Mean\ (1,000)$	2,339	1,130	1,691	145
$\%\triangle$	-59.30	3.13	1.52	-9.48
$\%\triangle$ at $t = 0$	-9.77	-4.40	6.55	-4.63
$\%\triangle$ at $t = 1$	-24.98	-2.77	5.41	-5.69
$\%\triangle$ at $t = 5$	-64.14	3.99	0.98	-9.81
$\%\triangle$ at $t = 9$	-82.86	11.23	-3.26	-13.76

Notes: Table is constructed using ARCOS Report 2 data (see Section 2.1 for details). The unit of analysis is state-quarter. Grams are adjusted for potency. See appendix (Table 7) for the active ingredients in each drug group. Estimates are based on Equation 1. All specifications include state and year fixed effects. State clustered standard errors are in parentheses. The 5th and 95th percentiles of the distribution of placebo estimates are in brackets. "Rank" is Florida's order and "Total" is the number of states (see Section 2.2). For $\%\triangle$ at $t = \#$ use $100 \times (e^{((Florida \times Post) + (Florida \times t \times Post))} - 1)$. *** p<0.01, ** p<0.05, * p<0.1

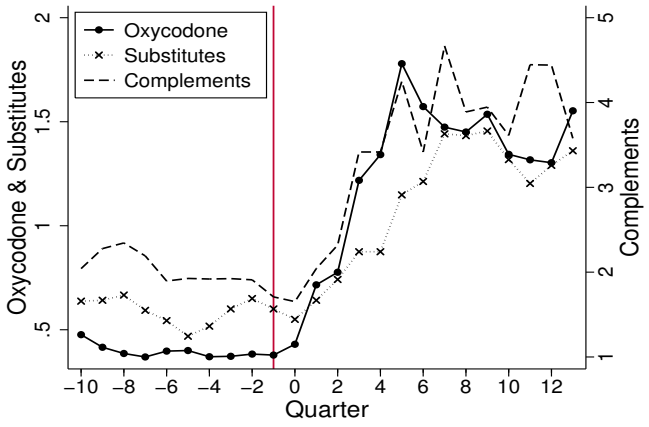


Figure 6: Quarterly Street Prices per Milligram in Florida 2008-2013

Notes: Figure is constructed using Bluelight and StreetRx data. Outliers are dropped. Substitutes category consist of hydrocodone only. Data points are a moving average of the previous, current, and following quarter's price per milligram. Quarters with missing data are imputed with year average for substitutes. Grams are adjusted for potency.

Table 2: Street Prices Per Milligram 2008-2012

	Oxycodone	Complements	Substitutes
Post	0.96***	2.31**	0.83***
P-value	0.00	0.03	0.00
Mean	0.40	2.04	0.59
N	220	55	49
%△	238.48	113.55	140.74

Notes: Table is constructed using StreetRx and Bluelight data. The unit of analysis is purchase-quarter. Outliers are dropped. Substitutes category consist of hydrocodone only. Grams are adjusted for potency. *** p<0.01, ** p<0.05, * p<0.1

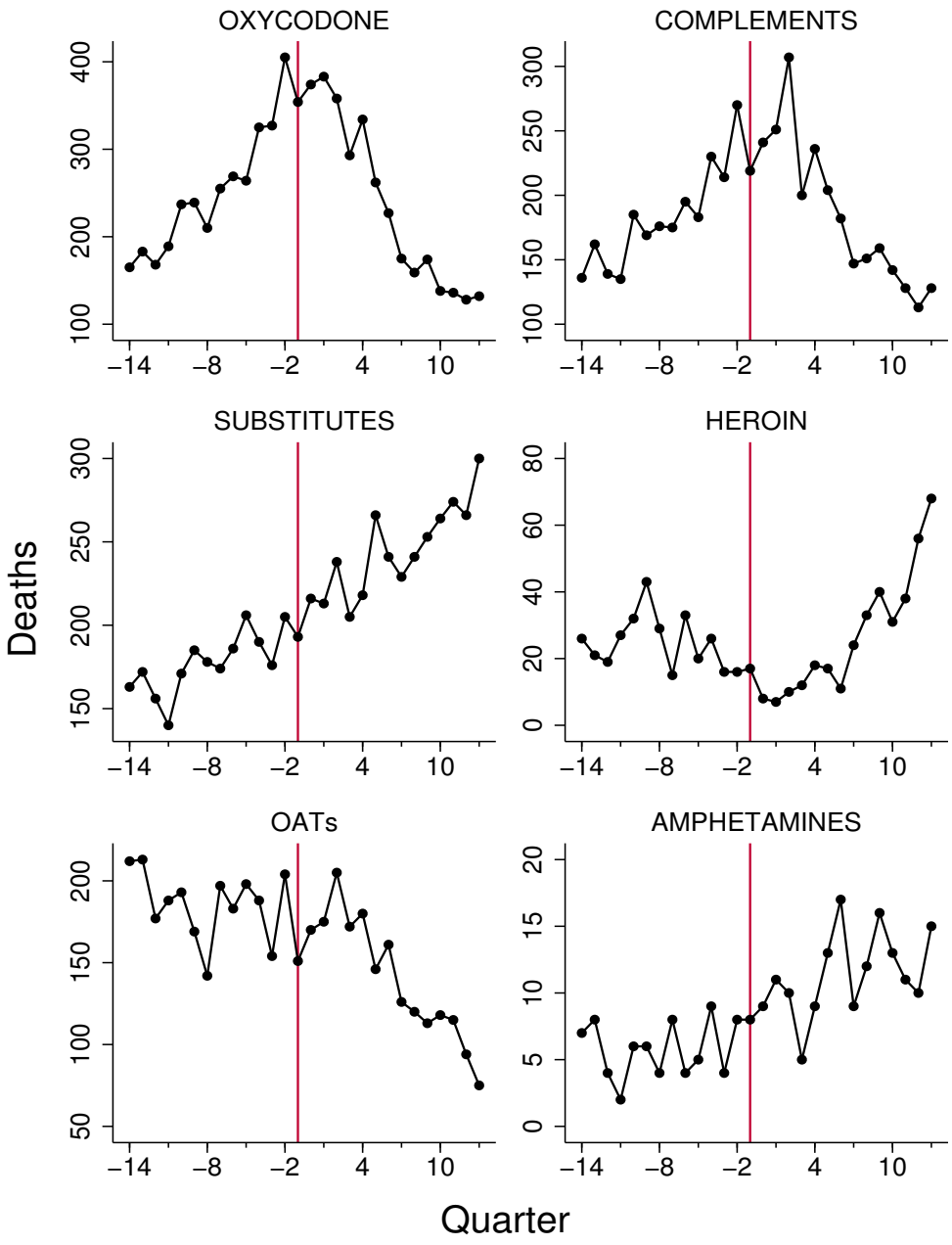


Figure 7: Causal Role in Death 2007-2013

Notes: Figure is constructed using Florida's Medical Examiners Commission data. Counts include deaths in which the drug played a causal role. See appendix (Table 7) for the active ingredients in each drug group.

Table 3: Log Deaths 2009-2012

	Oxycodone	Substitutes	OATs	Heroin	Comple.	Ampheta.	Cocaine
$PC \times t$	1.26	0.34	0.55	-0.37	0.93	-0.12	0.05
	(0.43)***	(0.34)	(0.40)	(0.23)	(0.40)**	(0.26)	(0.31)
$PC \times t \times Post$	-2.55	-0.19	-1.02	0.94	-1.92	0.22	-0.10
	(0.52)***	(0.42)	(0.36)***	(0.32)***	(0.47)***	(0.27)	(0.29)
$PC \times Post$	-1.95	0.10	-0.81	-1.77	0.09	0.36	-0.44
	(1.58)	(1.36)	(2.23)	(1.24)	(1.54)	(1.35)	(1.86)
t	0.01	0.00	-0.04	-0.00	-0.01	0.01	-0.01
	(0.02)	(0.01)	(0.02)**	(0.00)	(0.01)	(0.01)	(0.01)
$t \times Post$	-0.02	-0.00	0.03	0.00	0.01	-0.01	-0.00
	(0.02)	(0.02)	(0.02)*	(0.01)	(0.01)	(0.01)	(0.01)
$Post$	0.10	0.03	0.15	0.01	0.00	-0.02	0.14
	(0.08)	(0.07)	(0.08)	(0.02)	(0.06)	(0.04)	(0.06)
R^2	0.86	0.84	0.78	0.65	0.83	0.32	0.82
N	1,072	1,072	1,072	1,072	1,072	1,072	1,072
Level Mean	4.84	2.88	2.68	0.32	3.26	0.09	1.99

Notes: Table is constructed using Florida's Medical Examiners Commission data (see Section 2.1 for details). The unit of analysis is county-quarter. See appendix (Table 7) for the active ingredients in each drug group. Counts include deaths in which the drug played a causal role. Estimates are based on Equation 1. All specifications include county and year fixed effects. PC is a continuous variable that represents pain clinics per 1,000 population in a county pre-crackdown. County clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Log Hospital Discharges 2008-2012

	Opioids	Complements	Ampheta.	Marijuana	Cocaine	Heroin
Panel A: Inpatient Discharges						
$PC \times t$	0.52	0.26	0.59	0.22	-0.34	-0.10
	(0.22)**	(0.25)	(0.24)**	(0.20)	(0.21)	(0.14)
$PC \times t \times Post$	-1.06	-0.79	-0.42	-0.02	0.32	0.62
	(0.34)***	(0.36)**	(0.35)	(0.33)	(0.26)	(0.17)***
$PC \times Post$	-0.79	0.44	0.57	-1.94	2.19	-2.56
	(1.56)	(1.54)	(1.68)	(1.58)	(1.86)	(1.49)*
R^2	0.95	0.95	0.79	0.91	0.93	0.68
N	1,340	1,340	1,340	1,340	1,340	1,340
Level Mean	46.00	33.93	2.19	11.73	18.66	0.44
Panel B: Outpatient Emergency Department Discharges						
$PC \times t$	0.16	0.15	0.19	0.17	-0.56	-0.86
	(0.19)	(0.22)	(0.19)	(0.24)	(0.25)**	(0.22)***
$PC \times t \times Post$	-0.58	-0.58	0.06	0.03	0.52	1.26
	(0.30)*	(0.34)*	(0.28)	(0.39)	(0.36)	(0.26)***
$PC \times Post$	0.49	0.11	-0.72	-2.24	0.88	-0.20
	(1.53)	(1.37)	(1.26)	(1.47)	(1.82)	(1.56)
R^2	0.94	0.93	0.82	0.90	0.93	0.80
Level Mean	31.98	24.40	3.01	12.01	19.45	0.85

Notes: Table is constructed using discharge data collected by the Florida Agency for Healthcare Administration (see Section 2.1 for details). The unit of analysis is county-quarter. Drug groups are based on drug class and generated using the ICD-9-CM codes in Section 2.1. Estimates are based on Equation 1. All specifications include county and year fixed effects. PC is a continuous variable that represents pain clinics per 1,000 population in a county pre-crackdown. County clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

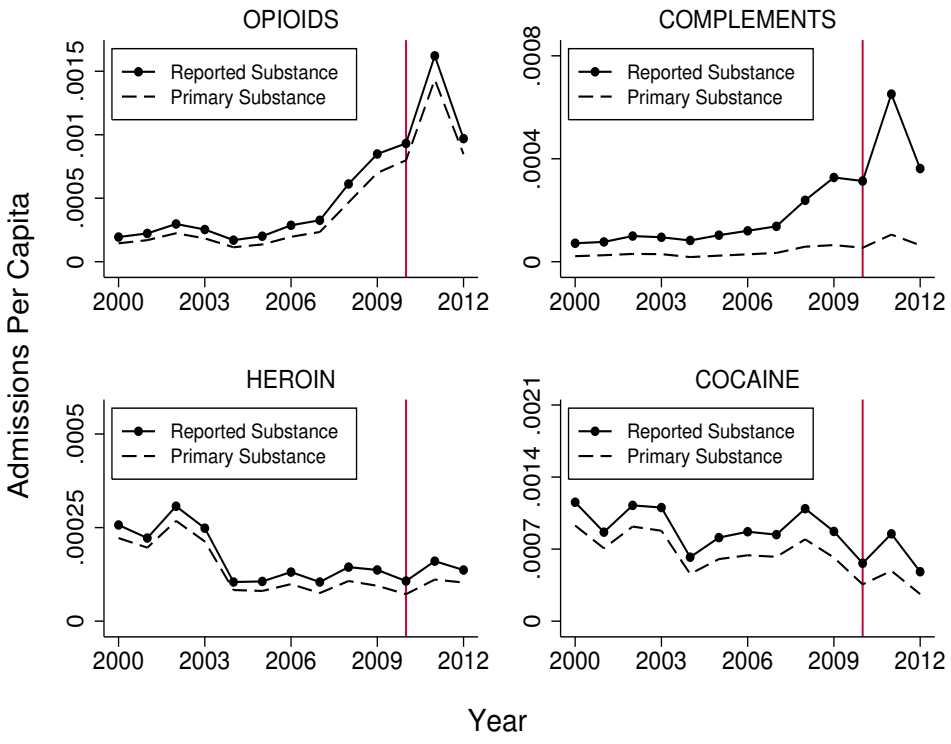


Figure 8: Substance Abuse Treatment Admissions in Florida 2007-2012

Notes: Figure is constructed using TEDS-A data (see Section 2.1 for details). Grams are divided by 2010 population estimates. "Primary Substance" includes admissions in which the substance is reported as the primary problem. "Reported Substance" includes admissions in which the substance is reported as a problem, reflecting co-abuse.

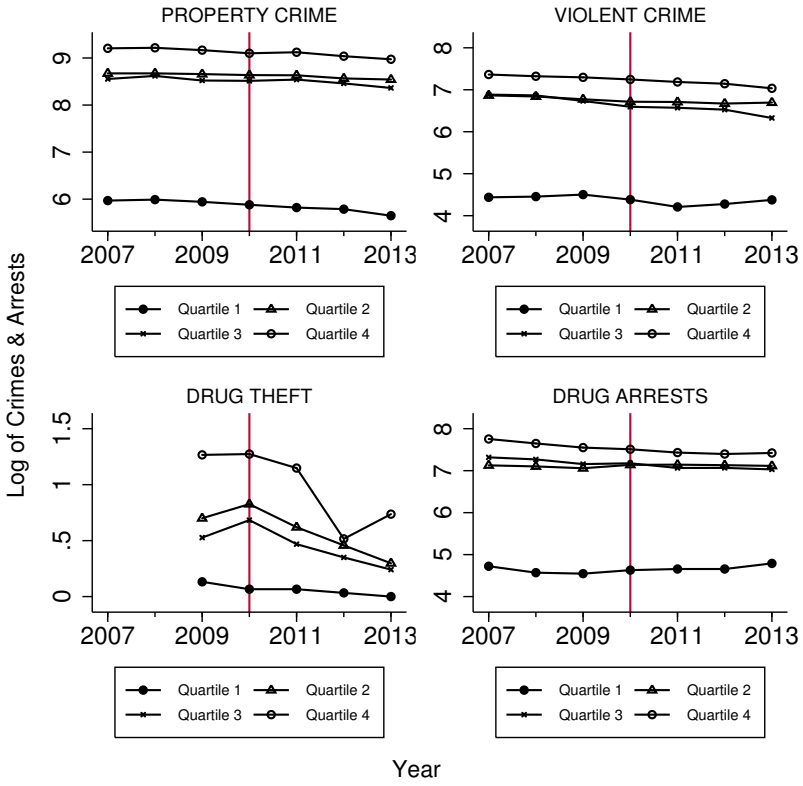


Figure 9: Log Crimes and Arrests by Pain Clinics Per Capita 2007-2013

Notes: Index crimes and drug arrests are constructed using data collected by the FDLE. Drug Theft is constructed using data collected by the DEA.

Table 5: Log Substance Abuse Treatment Admissions 2008-2012

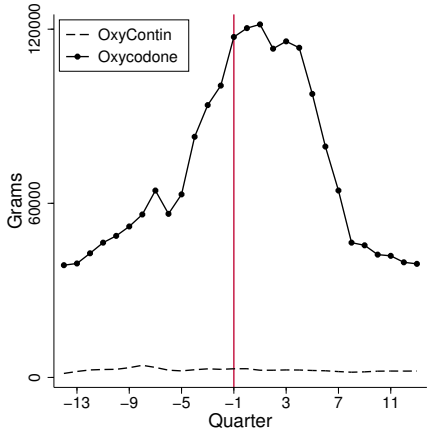
	Opioids	Comple.	Ampheta.	Heroin	Cocaine
Panel A: Florida vs. U.S. (Reported Substance)					
$Florida \times Post$	0.27	0.20	-0.13	-0.08	0.05
	(0.04)***	(0.07)***	(0.06)**	(0.07)	(0.04)
$rank/total$	42/48	39/48	18/48	24/48	27/48
$[p5, p95]$	[-0.40, 0.39]	[-0.53, 0.54]	[-0.56, 0.56]	[-0.50, 0.64]	[-0.58, 0.40]
R^2	0.97	0.96	0.97	0.97	0.98
N	240	240	240	240	240
$Level\ Mean$	14,992	5,513	669	2,434	15,837
$\%\triangle$	38.33	30.65	-13.91	-9.85	3.51
Panel B: Florida vs. Synthetic Florida (Reported Substance)					
$Florida \times Post$	0.29	0.36	0.18	0.25	0.23
$rank/total$	44/48	42/48	33/48	36/48	38/48
$[p5, p95]$	[-0.45, 0.35]	[-0.62, 0.71]	[-0.56, 0.49]	[-0.54, 0.60]	[-0.47, 0.49]
$rank^A/total^A$	42/43	40/43	30/43	34/43	35/43
$[p5, p95]^A$	[-0.44, 0.24]	[-0.58, 0.39]	[-0.56, 0.49]	[-0.52, 0.38]	[-0.41, 0.41]
$\%\triangle$	33.26	42.91	19.98	28.59	25.83
Panel C: Florida vs. U.S. (Primary Substance)					
$Florida \times Post$	0.36	0.14	0.11	-0.05	-0.02
	(0.04)***	(0.07)*	(0.07)	(0.08)	(0.05)
$rank/total$	45/48	37/48	34/48	25/48	24/48
$[p5, p95]$	[-0.40, 0.36]	[-0.57, 0.79]	[-0.63, 0.86]	[-0.71, 0.56]	[-0.43, 0.46]
R^2	0.97	0.95	0.95	0.97	0.97
N	240	240	240	240	240
$Level\ Mean$	12,317	1,109	161	1,717	11,095
$\%\triangle$	52.03	18.47	13.60	-5.97	-1.25

Notes: Table is constructed TEDS-A data (see Section 2.1 for details). DC, Georgia, and Mississippi are dropped due to non-reporting on several years. The unit of analysis is state-year. "Primary Substance" includes admissions in which the given substance is reported as the primary problem. "Reported Substance" includes admissions in which the given substance is reported as a problem (includes "Primary Substance"). Estimates in Panels A and C are based on Equation 2 and include state fixed effects (See Appendix A.4 for graphical evidence on parallel trends). State clustered standard errors are in parentheses. The 5th and 95th percentiles of the distribution of placebo estimates are in brackets. "Rank" is Florida's order and "Total" is the number of states. Percentiles, ranks, and totals labeled A are adjusted by excluding states where the synthetic control method failed to generate an appropriate counterfactual (see Section 2.2). For $\%\triangle$ in Panel A and C use $100 \times (e^{((Post)+(Florida \times Post))} - e^{(Post)})$. For $\%\triangle$ in Panel B use $100 \times (e^{(}Florida \times Post) - 1)$. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Log Index Crimes, Arrests, and Drug Theft 2008-2012

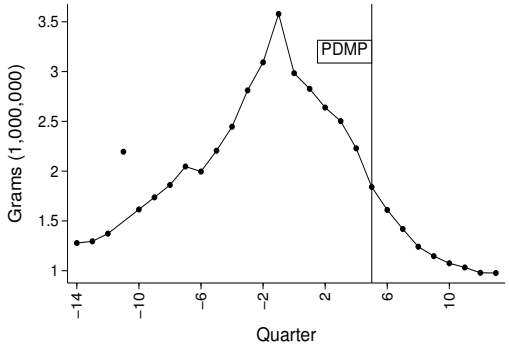
	Drug Arrests	Property Crime	Violent Crime	Drug Theft
Panel A: State Level Analysis (Florida vs. U.S.)				
$Florida \times Post$	-0.05	-0.07	-0.13	-0.56
	(0.09)	(0.01)***	(0.02)***	(0.07)***
$Rank/Total$	11/49	5/49	1/49	5/49
$[p5, p95]$	[-0.30, 0.34]	[-0.08, 0.09]	[-0.10, 0.20]	[-0.68, 0.60]
R^2	0.94	1.00	1.00	0.90
N	245	245	245	196
$Level\ Mean$	149,267	713,326	113,925	114
$\%\triangle$	-4.52	-6.62	-11.70	-40.69
Panel B: State Level Analysis (Florida vs. Synthetic Florida)				
$Florida \times Post$	0.12	-0.07	-0.08	-0.62
$Rank/Total$	30/49	7/49	7/49	5/49
$[p5, p95]$	[-0.36, 0.80]	[-0.09, 0.07]	[-0.09, 0.12]	[-0.77, 0.63]
$Rank^A/Total^A$	28/44	5/44	6/44	3/44
$[p5, p95]^A$	[-0.30, 0.80]	[-0.09, 0.07]	[-0.09, 0.08]	[-0.55, 0.63]
$\%\triangle$	13.07	-6.40	-7.83	-46.32
Panel C: County Level Analysis				
$PC \times Post$	-1.86	-0.74	0.98	-5.89
	(1.29)	(0.80)	(1.19)	(2.37)**
R^2	0.99	1.00	0.99	0.74
N	330	330	330	264
$Level\ Mean$	2,261	10,796	1,724	2

Notes: Table is constructed using data collected by the FDLE, the DEA, and the FBI. Hawaii and DC are dropped due to substantial missing values. The unit of analysis is state-year. Estimates are based on Equation 2 and include state fixed effects (See Appendix A.4 for evidence on parallel trends). PC is a continuous variable that represents pain clinics per 1,000 population in a county pre-crackdown. State (Panel A) and county (Panel C) clustered standard errors are in parentheses. The 5th and 95th percentiles of the distribution of placebo estimates are in brackets. "Rank" is Florida's order and "Total" is the number of states. Percentiles, ranks, and totals labeled A are adjusted by excluding states where the synthetic control method failed to generate an appropriate counterfactual (see Section 2.2). For $\%\triangle$ in Panel A use $100 \times (e^{((Post)+(Florida \times Post))} - e^{(Post)})$. For $\%\triangle$ in Panel B use $100 \times (e^{(}Florida \times Post) - 1)$. *** p<0.01, ** p<0.05, * p<0.1



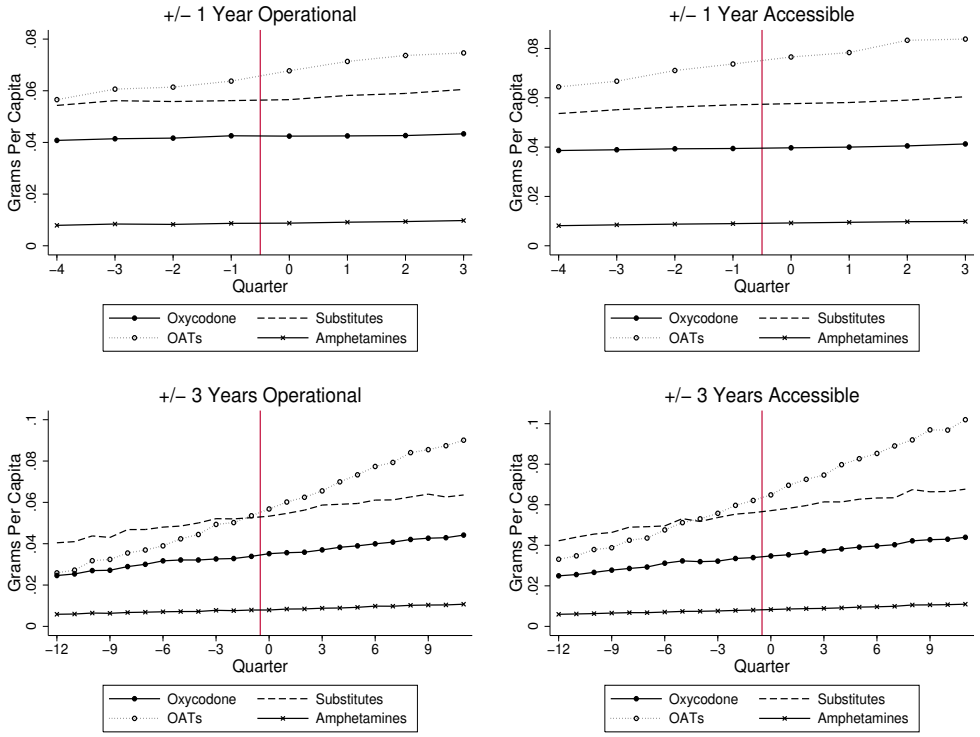
Notes: Figure is constructed using data from the Drug Utilization Reports for the Florida Medicaid Program. The y-axis captures the total number of grams of oxycodone National Drug Codes (NDCs) for NDCs with $1,000 or more in claims. Grams are classified into those from OxyContin NDCs and those from non-reformulated oxycodone NDCs.

Figure 10: Oxycodone Purchases by Florida Medicaid 2007-2013



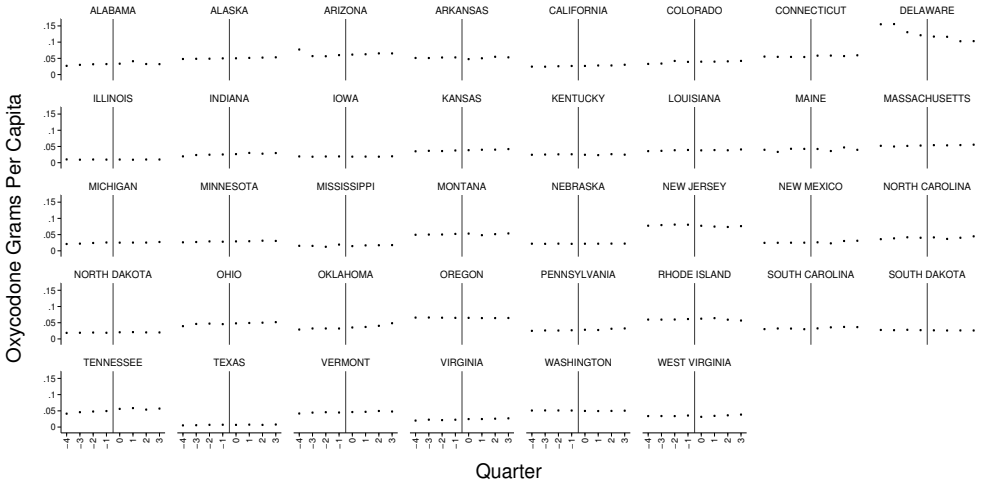
Notes: Figure is constructed using ARCOS Report 2 data. The vertical line marks the fourth quarter of 2011, when registered healthcare providers began accessing the PDMP.

Figure 11: Prescription Drug Monitoring Program in Florida



Notes: Figure is constructed using ARCOS Report 2 data (see Section 2.1 for details). Grams are adjusted for potency and divided by 2010 population estimates. See appendix (Table 7) for the active ingredients in each drug group. The vertical line marks the time a PDMP became operational or the time a PDMP became accessible to registered healthcare providers in a given state. Graphs are based on balanced panels.

Figure 12: PDMP Implementation by Drug Group and Time Window



Notes: Figure is constructed using ARCOS Report 2 data (see Section 2.1 for details). Grams are divided by 2010 population estimates. The vertical line marks the time a PDMP became accessible to registered healthcare providers in a given state. Graphs are based on balanced panels.

Figure 13: Prescription Drug Monitoring Program by State

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A Appendix

A.1 Active Ingredients and Equianalgesic Opioid Dosing

Table 7: Active Ingredient Per Drug Group

Drug Group	Active Ingredient	Comments
1) Oxycodone	Oxycodone	Opioid. Schedule II.
2) Prescription Substitutes	Hydrocodone Morphine Oxymorphone Hydromorphone Fentanyl Codeine Meperidine	Opioids. Other controlled opioid pain relievers not used in medication-assisted treatment of opioid addiction.
3) Illegal Substitutes	Heroin	Opioid. Schedule I.
4) Other Illegal	Cocaine Marijuana	
5) Opioid Abuse Treatment (OATs)	Methadone Buprenorphine	Opioids. FDA-approved medications for opioid dependence treatment. (SAMHSA, 2011).
6) Prescription Complements	Alprazolam	Benzodiazepine. Schedule IV. Co-abused with opioids. (Jones et al., 2012)
7) Amphetamine	Amphetamine	Stimulant. Schedule II.

The equianalgesic chart used in this study (see Table 8) is drawn from McPherson (2009). This chart lists equivalent doses for various analgesics and is used to convert the active ingredients in OAT and Prescription Substitutes into oxycodone potency units. Note that the equivalence changes not only because of the active ingredient, but also because of the route of administration. Since ARCOS data provides total gram information by active ingredient, but does not specify the formulation, this

study assumes oral doses when possible and transdermal doses when not. A highly potent drug does not necessarily translate into a preferred drug among non-medical users because side effects and euphorigenic properties can vary.

Table 8: Equianalgesic Opioid Dosing

Drug	Route	Mg	Drug	Route	Mg
Oxycodone	Oral	20	Methadone (30-90)	Oral	7.5
Fentanyl	Transdermal	0.36	Methadone (90-300)	Oral	5
Oxymorphone	Oral	10	Methadone (>300)	Oral	3.75
Oxymorphone	IV	1	Hydrocodone	Oral	30
Morphine	Oral	30	Hydromorphone	Oral	7.5
Morphine	IV	10	Hydromorphone	IV	1.5
Codeine	Oral	200	Meperidine	Oral	300
Codeine	IV	100	Meperidine	IV	100
Tramadol	Oral	120	Tramadol	IV	100
Buprenorphine	Sublingual	0.4	Buprenorphine	IV	0.3
Buprenorphine	Transdermal	0.43	Fentanyl	IV	0.1

A.2 Healthcare Providers

This section examines suppliers, supply, and supply per supplier by provider type, an analysis that shows whether supply reductions can be explained by changes in the intensive or the extensive margin.

Figure 14 plots prescription drug grams purchased by dispensing practitioners and pharmacies and the number of dispensing practitioners and pharmacies purchasing these grams. Post-crackdown, both outcomes declined abruptly for dispensing practitioners. This suggests the extensive margin, that is, the number of suppliers, played an important role in the formation and dissolution of the epidemic in the case

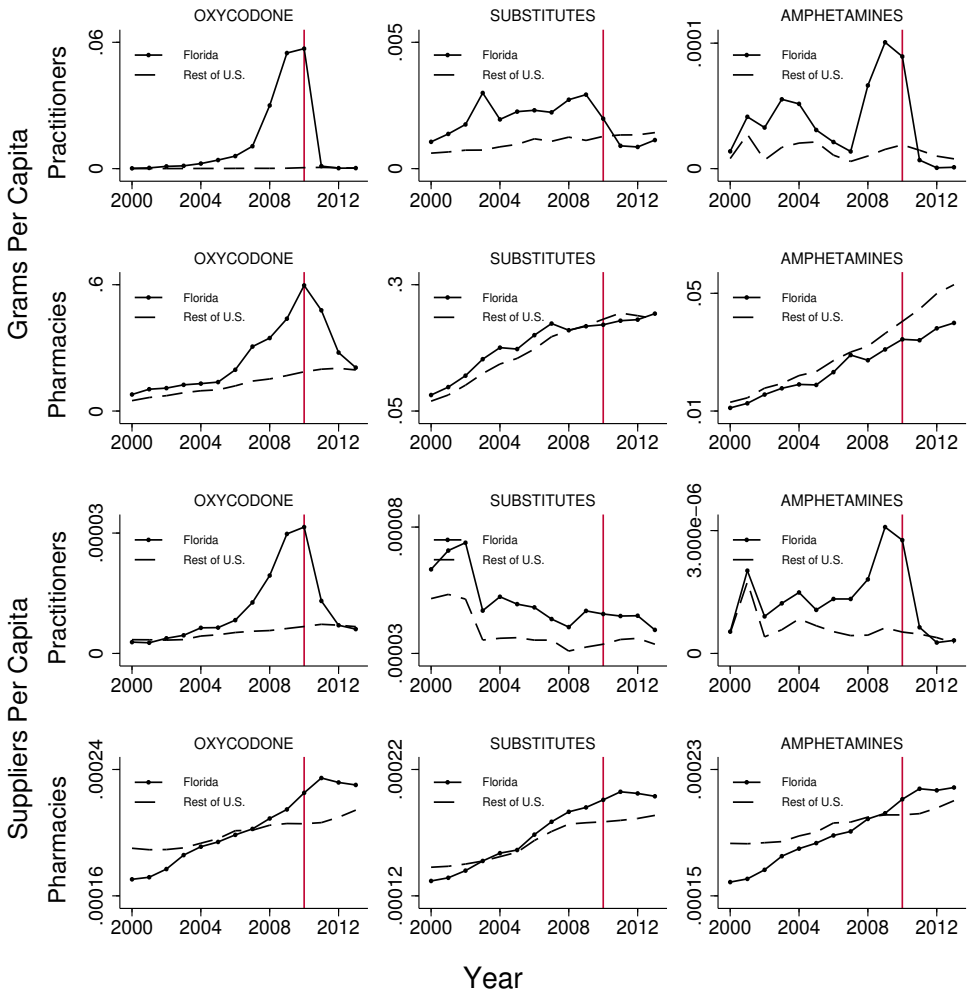


Figure 14: Supply and Suppliers by Healthcare Provider 2000-2013

Notes: Figure is constructed using ARCOS Report 5 (see Section 2.1 for details). Outcomes are divided by 2010 population estimates, and grams are adjusted for potency. See appendix (Table 7) for the active ingredients in each drug group. Suppliers represent total healthcare providers purchasing grams of the named substance for retail sale. Because the unit of observation is aggregated at the type of provider-level rather than at the individual provider-level, suppliers in substitute category represent an average of purchasing providers among drugs in this group.

of dispensing practitioners. Other drug groups, including stimulants, display similar patterns. These results are consistent with the implementation of tighter dispensing practitioner laws or with a shock to distributors.[56]

As for pharmacies, there is an abrupt trend break in supply, while supplier size continued to increase over the following year but then declined. Various components of the intervention could explain these results. First, the DEA fined and revoked the registration of a number of pharmacies, including large chain pharmacies such as CVS and Walgreens. This action could have affected supply not only through incapacitation, but also through deterrance of other pharmacies. A second story could be a shock to distributors. Finally, findings could be explained by the effect of supply-side interventions on physicians operating from pain clinics. Since pharmacies cannot dispense without a physician's prescription, a shock to oxycodone supply might be explained by incapacitated or deterred physicians.

A.3 Spillovers

This section explores whether the crackdown in Florida resulted in supply spillovers to other states. Spillovers would occur if prescription drug diversion shifted to other states. The econometric model is depicted below. Equation 3 estimates a slope and intercept, pre and post-crackdown, for Florida Fl_g, neighboring states Nbr_g, and the rest of the nation US_g.

[56]Note that a sharp decline in the number of dispensing practitioners does not translate into a sharp decline in the number of practitioners operating in Florida. Practitioners could still prescribe and administer drugs as long as their medical licenses/DEA registrations remained active.

$$Y_{gy} = \beta_1 Fl_g + \alpha_1 Nbr_g + \mu_1 US_g + \beta_2 Fl_g Post_y + \alpha_2 Nbr_g Post_y + \mu_2 US_g Post_y + \beta_3 Fl_g t_y + \alpha_3 Nbr_g t_y + \mu_3 US_g t_y + \beta_4 Fl_g t_y Post_y + \alpha_4 Nbr_g t_y Post_y + \mu_4 US_g t_y Post_y + \epsilon_{gy} \quad (3)$$

Table 9 reports estimates from Equation 3 for outcomes Y_{gy} measured in levels and logs. Depending on the specification, the dummy variable US_g takes the value zero for (1) only Florida –baseline–; (2) Florida and adjacent states Georgia and Alabama; or (3) Florida and nearby states Georgia, Alabama, Mississippi, Tennessee, North Carolina, and South Carolina.

Regardless of how Nbr_g is selected or whether outcomes are measured in levels or logs, estimates of the rest of the nation US_g remain nearly identical. This should ease any concerns of spillovers biasing results from Equations 1 and 2. Nonetheless, adjacent states do display a small intercept increase α_2 post-crackdown.

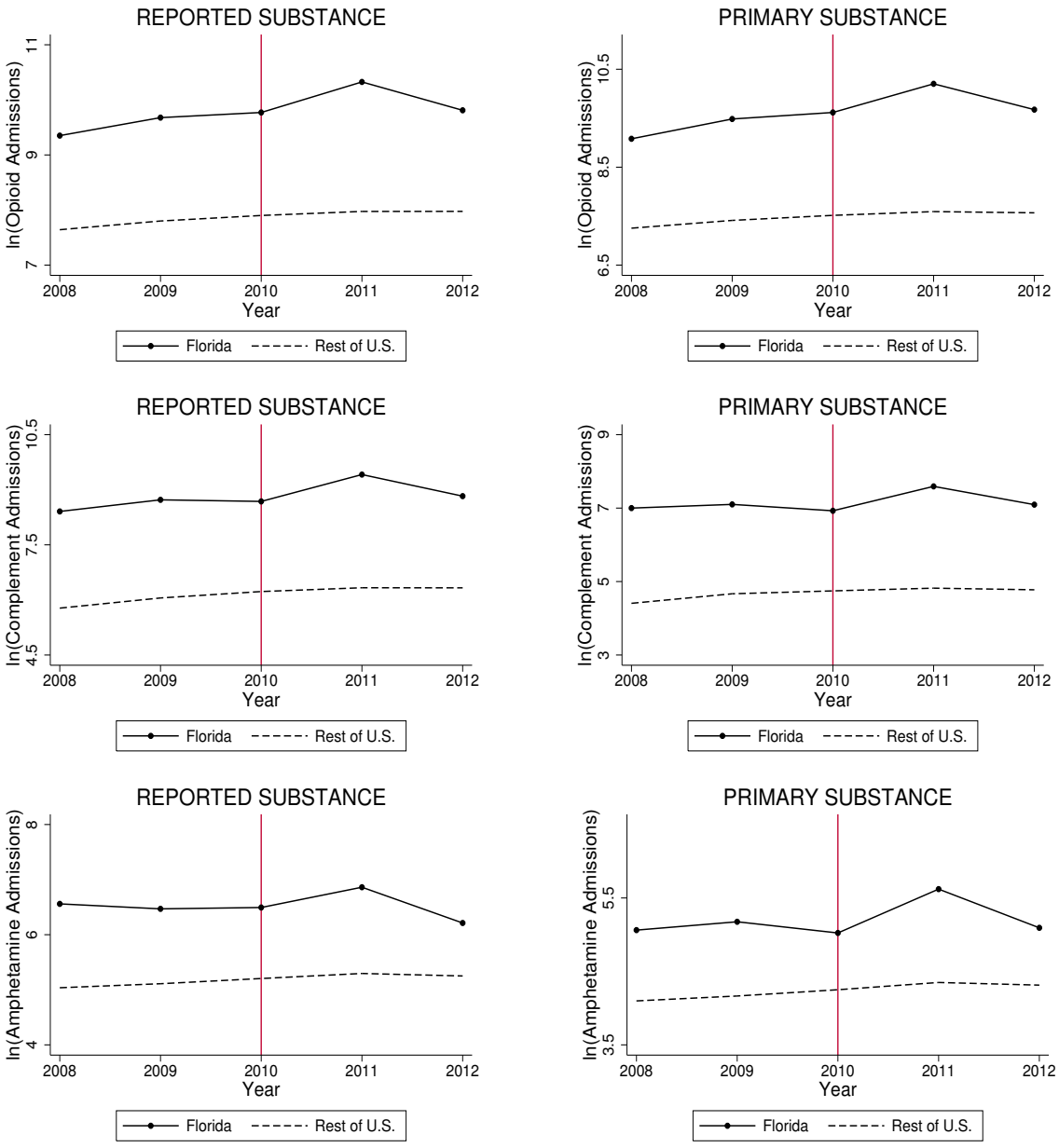
A.4 Parallel Trends and Other Graphs and Tables

Diff-in-diff estimates rely on the parallel trends assumption. To evaluate the validity of this assumption, this section provides graphical evidence for the main estimates of interest that are based on Equation 2. Figure 15 plots outcomes in Table 5, Panel C –Primary Substance– and Panel A –Reported Substance–. Figure 16 plots outcomes in Table 6, Panel A.

Table 9: Quarterly Oxycodone Grams 2008-2012

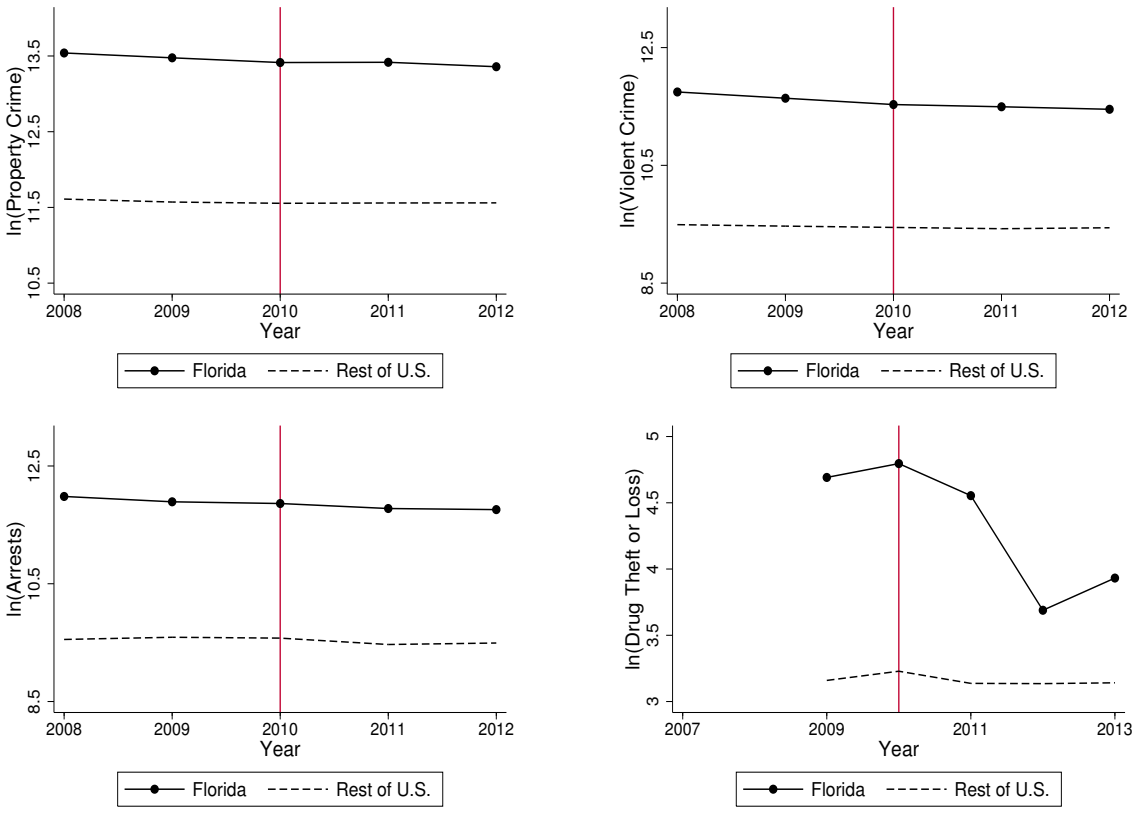
	Level			Logs		
		Adjacent	Nearby		Adjacent	Nearby
Fl	3449.64	3449.64	3449.64	15.10	15.10	15.10
	(149.66)	(149.96)	(149.96)	(0.04)	(0.04)	(0.04)
$Fl \times Post$	-402.35	-402.35	-402.35	-0.10	-0.10	-0.10
	(154.47)	(154.77)	(154.77)	(0.05)	(0.05)	(0.05)
$Fl \times t$	201.95	201.95	201.95	0.08	0.08	0.08
	(21.78)	(21.83)	(21.83)	(0.01)	(0.01)	(0.01)
$Fl \times t \times Post$	-424.97	-424.97	-424.97	-0.20	-0.20	-0.20
	(23.15)	(23.19)	(23.19)	(0.01)	(0.01)	(0.01)
Nbr		309.29	333.81		12.57	12.53
		(50.96)	(45.74)		(0.18)	(0.19)
$Nbr \times Post$		10.91	-7.36		0.02	-0.03
		(70.01)	(63.03)		(0.24)	(0.25)
$Nbr \times t$		11.31	11.37		0.04	0.04
		(7.14)	(6.74)		(0.03)	(0.03)
$Nbr \times t \times Post$		-6.93	-4.35		-0.02	-0.02
		(10.82)	(10.81)		(0.04)	(0.04)
$U.S.$	261.37	259.37	251.49	12.00	11.97	11.92
	(22.21)	(23.07)	(24.38)	(0.10)	(0.11)	(0.11)
$U.S. \times Post$	-0.76	-1.25	0.14	0.00	-0.00	0.00
	(30.22)	(31.38)	(33.12)	(0.14)	(0.14)	(0.15)
$U.S. \times t$	6.43	6.22	5.75	0.02	0.02	0.02
	(3.35)	(3.48)	(3.68)	(0.02)	(0.02)	(0.02)
$U.S. \times t \times Post$	-3.89	-3.76	-3.82	-0.01	-0.01	-0.01
	(5.16)	(5.36)	(5.64)	(0.02)	(0.02)	(0.03)
R^2	0.75	0.75	0.75	0.99	0.99	0.99
N	1,020	1,020	1,020	1,020	1,020	1,020

Notes: Table is constructed using ARCOS Report 2 data (see Section 2.1 for details). Adjacent states include Georgia and Alabama. Nearby states include Georgia, Alabama, Mississippi, Tennessee, North Carolina, and South Carolina. Robust standard errors are in parenthesis.



Notes: Figure is constructed using TEDS-A data (see Section 2.1 for details).

Figure 15: Log of Substance Abuse Treatment Admissions 2008-2012



Notes: Index crimes and drug arrests are constructed using data collected by the Federal Bureau of Investigation. Drug Theft is constructed using data collected by the Drug Enforcement Administration (see Section 2.1 for details).

Figure 16: Log of Crimes and Drug Arrests 2008-2012

Table 10: Deaths 2009-2012

	Oxycodone	Substitute	OATs	Heroin	Complement	Ampheta.	Cocaine
t	18.21	2.40	-0.52	-2.24	8.22	0.22	2.23
	(3.55)	(0.92)	(2.69)	(0.63)	(2.62)	(0.16)	(2.14)
$t \times Post$	-45.81	1.48	-7.73	5.48	-22.30	0.42	-4.00
	(4.43)	(1.32)	(3.33)	(0.88)	(4.13)	(0.31)	(2.40)
$Post$	9.41	14.95	18.82	-9.02	24.38	0.84	11.97
	(27.12)	(10.07)	(21.65)	(3.40)	(28.69)	(1.81)	(13.12)
$Constant$	388.67	199.60	175.07	12.40	246.80	7.40	140.39
	(23.06)	(7.18)	(17.55)	(2.56)	(18.61)	(1.17)	(12.04)
Lives Saved	1967.21	-216.00	159.48	-139.15	759.82	-27.18	60.11

Notes: Table is constructed using Florida's Medical Examiners Commission data (see Section 2.1 for details). The unit of analysis is state-quarter-drug. See appendix (Table 7) for the active ingredients in each drug group. Counts include deaths in which the drug played a causal role.

A.5 Prescription Drug Monitoring Program

As discussed in Section 3.4, Florida's Prescription Drug Monitoring Program became operational –providers start reporting to the database– in September of 2011 and accessible –providers start searching the database– in October of 2011 (See Figure 11). Meanwhile, Oxycodone's dramatic trend break was observed starting in July of 2010. This timeline of events should ease concerns regarding the PDMPs importance in the Florida context. To provide further evidence, I estimate the effect of PDMPs on prescription drug supply in states other than Florida. I combine ARCOS Report 2 data from 2000-13 and exploit the timing a PDMP became operational and accessible (see Table 13).[57]

$$Y_{sq} = \alpha_0 + \alpha_1 PDMP_{sq} + \alpha_2 PDMP_{sq} * t_q + \alpha_3 t_q + S_s + Y_q + \epsilon_{sq} \tag{4}$$

Equation 4 is the general econometric specification. Y_{sq} measures grams per capita and is indexed by state s and quarter q. All specifications include state S_s and year Y_q fixed effects. $PDMP_{sq}$ is the prescription drug monitoring program treatment variable and is equal to one if the state has an operational (or accessible) PDMP in quarter q. t_q is a linear trend that reflects the number of periods before or after the timing of PDMP implementation and is coded as (...-3, -2, -1, 0, 1, 2, 3,...). t_q is interacted with $PDMP_{sq}$ to account for any changes in the slope of t_q after

[57] I constructed Table 13 by contacting PDMP administrators in all states and/ or reading their PDMP documentation. The table provides two types of dates: (1) date operational O, when healthcare providers began reporting to the PDMP, and (2) date accessible A, when healthcare providers began to search the database. In vey few occasions, the date a PDMP became operational might represent the date a PDMP became electronic. Specifically, some states implemented non-electronic versions of the PDMP in or before the 90's, but report the time a PDMP becomes electronic as the implementation date.

PDMP implementation. Estimates based on Equation 4 but that also include state specific linear trends t_{sq} and $PDMP_{st} * t_{sq}$, are reported as a robustness check. States with no variation in $PDMP_{sq}$ during the sample period are dropped. Standard errors are clustered at the state level.

Figure 12 plots potency adjusted grams per capita for each prescription drug group using a balanced panel of states at different time windows. The time window +/- 1 Year includes treated states up to one year before and after the PDMP, +/- 2 Years includes treated states up to two years before and after the PDMP, and +/- 3 Years includes treated states up to three years before and after the PDMP. There appears to be no slope or intercept break after a PDMP becomes operational or accessible.

Tables 11 and 12 report estimates from Equation 4 for different time windows, drug groups, balanced and unbalanced panels, and set of controls. The former exploits the time a PDMP became operational, while the latter exploits the time a PDMP became accessible. Regardless of how the data is selected, all estimates are statistically insignificant and suggest that PDMP implementation has no effect on prescription drug supply. While this analysis is by no means a comprehensive study of PDMP's effectiveness, as PDMPs might be effective in selected contexts, it should alleviate any concerns regarding the PDMP generating the substantial decline in prescription drug grams observed in Florida.

Table 11: PDMP Operational

	+/- 3 Year Window				+/- 2 Year Window				+/- 1 Year Window			
Panel A: Oxycodone - Quarterly Grams Per 1,000 Population												
$PDMP$	-1.92	-1.42	-0.86	-0.52	-0.79	-0.77	-0.96	-0.62	0.50	-0.08	0.40	-0.29
	(1.30)	(0.98)	(0.95)	(0.76)	(0.95)	(1.06)	(1.09)	(0.95)	(0.77)	(1.12)	(0.89)	(1.30)
$Mean$	40.06	40.06	29.86	29.86	41.70	41.70	39.84	39.84	42.84	42.84	41.61	41.61
Panel B: Substitutes - Quarterly Grams Per 1,000 Population												
$PDMP$	-0.19	0.01	0.02	0.30	0.15	0.40	0.41	0.48	0.43	-0.30	0.62	-0.23
	(0.83)	(0.81)	(1.23)	(1.20)	(0.97)	(0.92)	(1.09)	(1.07)	(0.58)	(0.89)	(0.58)	(0.99)
$Mean$	52.31	52.31	47.11	47.11	54.07	54.07	52.81	52.81	55.45	55.45	55.63	55.63
Panel C: OATs - Quarterly Grams Per 1,000 Population												
$PDMP$	1.39	1.53	1.27	1.18	1.75	0.60	1.49	0.36	1.92	2.14	1.62	1.88
	(1.29)	(1.03)	(1.84)	(0.93)	(1.24)	(0.81)	(1.41)	(0.77)	(1.99)	(1.31)	(2.13)	(1.30)
$Mean$	58.19	58.19	39.05	39.05	62.21	62.21	55.50	55.50	67.06	67.06	60.58	60.58
Panel D: Amphetamines - Quarterly Grams Per 1,000 Population												
$PDMP$	-0.02	0.03	-0.17	-0.09	0.01	0.00	-0.06	-0.04	-0.07	-0.08	-0.16	-0.14
	(0.13)	(0.11)	(0.14)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.14)	(0.15)	(0.13)	(0.14)
$Mean$	8.14	8.14	6.91	6.91	8.48	8.48	7.81	7.81	8.86	8.86	8.32	8.32
$Clusters$	32	32	20	20	32	32	28	28	32	32	29	29
N	709	709	480	480	492	492	448	448	252	252	232	232
$Trend_t$	X		X		X		X		X		X	
$Trend_{st}$		X		X		X		X		X		X
$Balanced$			X	X			X	X			X	X

Notes: Table is constructed using ARCOS Report 2 data (see Section 2.1 for details). Grams are adjusted for potency. See appendix (Table 7) for the active ingredients in each drug group. Estimates are based on Equation 4. All specifications include state and year fixed effects. State clustered standard errors are in parentheses.

Table 12: PDMP Accessible

	+/- 3 Year Window				+/- 2 Year Window				+/- 1 Year Window			
Panel A: Oxycodone - Quarterly Grams Per 1,000 Population												
$PDMP$	-1.51	-0.91	-0.78	-0.52	-0.63	-0.37	-0.30	-0.18	0.63	0.46	0.69	0.40
	(0.82)	(0.59)	(0.69)	(0.59)	(0.50)	(0.43)	(0.39)	(0.41)	(0.64)	(0.59)	(0.79)	(0.69)
$Mean$	38.29	38.29	29.81	29.81	39.66	39.66	34.37	34.37	40.39	40.39	39.07	39.07
Panel B: Substitutes - Quarterly Grams Per 1,000 Population												
$PDMP$	-0.40	-0.13	0.06	0.09	0.35	0.37	0.74	0.61	-0.12	-0.48	-0.18	-0.61
	(0.58)	(0.58)	(0.77)	(0.79)	(0.62)	(0.65)	(0.73)	(0.78)	(0.69)	(0.70)	(0.72)	(0.75)
$Mean$	52.78	52.78	49.65	49.65	54.49	54.49	53.08	53.08	55.56	55.56	55.54	55.54
Panel C: OATs - Quarterly Grams Per 1,000 Population												
$PDMP$	1.01	1.28	1.70	1.71	1.24	0.40	1.04	0.48	-0.42	0.02	-1.41	-1.52
	(1.08)	(1.00)	(1.46)	(1.20)	(0.80)	(0.85)	(0.82)	(0.66)	(1.39)	(1.56)	(1.44)	(1.62)
$Mean$	64.42	64.42	46.68	46.68	68.58	68.58	55.98	55.98	73.24	73.24	68.97	68.97
Panel D: Amphetamines - Quarterly Grams Per 1,000 Population												
$PDMP$	0.10	0.12	0.07	0.06	0.17	0.14	0.09	0.10	0.06	0.09	-0.01	0.07
	(0.11)	(0.10)	(0.10)	(0.11)	(0.09)	(0.10)	(0.09)	(0.11)	(0.12)	(0.15)	(0.13)	(0.16)
$Mean$	8.24	8.24	7.00	7.00	8.60	8.60	7.49	7.49	8.98	8.98	8.59	8.59
$Clusters$	42	42	26	26	42	42	33	33	42	42	38	38
N	916	916	624	624	637	637	528	528	330	330	304	304
$Trend_t$	X		X		X		X		X		X	
$Trend_{st}$		X		X		X		X		X		X
$Balanced$			X	X			X	X			X	X

Notes: Table is constructed using ARCOS Report 2 data (see Section 2.1 for details). Grams are adjusted for potency. See appendix (Table 7) for the active ingredients in each drug group. Estimates are based on Equation 4. All specifications include state and year fixed effects. State clustered standard errors are in parentheses.

Table 13: Prescription Drug Monitoring Program Key Dates

State	O-Year	O-Mo.	A-Year	A-Mo.	State	O-Year	O-Mo.	A-Year	A-Mo.
Alabama	2006	4	2007	8	Montana	2012	3	2012	11
Alaska	2011	8	2012	1	Nebraska	2009	3	2011	4
Arizona	2008	10	2008	12	Nevada	1997	1	1997	4
Arkansas	2013	3	2013	3	New Hampshire	2014	7	2014	7
California	1939		2009	1	New Jersey	2011	9	2012	1
Colorado	2007	7	2008	2	New Mexico	2005	8	2005	8
Connecticut	2008	7	2008	7	New York	1973	4		
Delaware	2012	3	2012	8	North Carolina	2007	7	2007	10
Florida	2011	9	2011	10	North Dakota	2007	9	2007	9
Georgia	2013	5	2013	5	Ohio	2006	7	2006	10
Hawaii	1943				Oklahoma	1991		2006	7
Idaho	1997	10	1998	3	Oregon	2011	6	2011	9
Illinois	1999	8	2007		Pennsylvania	2002	1	2002	1
Indiana	1994		2007	1	Rhode Island	1979		2012	9
Iowa	2009	3	2009	3	South Carolina	2008	2	2008	6
Kansas	2010	7	2010	7	South Dakota	2011	12	2012	3
Kentucky	1999		2005	3	Tennessee	2006	12	2006	12
Louisiana	2008	8	2009	1	Texas	1982		2001	9
Maine	2004	7	2005	1	Utah	1997	1	1997	1
Maryland	2013	8	2013	8	Vermont	2009	1	2009	4
Massachusetts	1992	4	2010	12	Virginia	2006	6	2006	6
Michigan	1988	1	2007	4	Washington	2011	10	2012	1
Minnesota	2010	1	2010	4	West Virginia	1996		2004	12
Mississippi	2005	12	2005	12	Wisconsin	2013	6	2013	6
Missouri	N/A	N/A	N/A	N/A	Wyoming	2004	10	2013	7