The Effect of Prescription Drug Monitoring Programs on Opioid Prescriptions and Heroin Crime Rates

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September 13, 2018

Abstract

In response to abuse of prescription opioids, 50 U.S. states have implemented electronic prescription drug monitoring programs (PDMPs) that record opioid prescriptions into state registries. This paper uses a difference-in-differences framework and interactive fixed effects factor models to identify the effect of PDMPs on opioid painkiller prescriptions filled and on rates of heroin crimes. PDMP databases caused an 8% decrease in oxycodone shipments, driven by large decreases in high dosage pills. PDMPs have heterogeneous effects on heroin crime incidents depending on counties' pre-policy levels of prescription opioids per capita, with an 49-89% increase in heroin crime within more opioid-dense counties.

1 Introduction

The United States is in the midst of an opioid drug epidemic, which the Center for Disease Control has classified as a top public health concern, calling it "the worst drug epidemic in US history." An estimated 2 million Americans suffer from a prescription painkiller abuse disorder and 470,000 suffer from heroin abuse.[1] Increasing overdose deaths have surpassed fatal car accidents as the leading cause of accidental death and have contributed to the recent historic reversal in mid-life mortality among non-Hispanic white Americans documented in Case and Deaton (2015).

In response to rising rates of opioid abuse and overdoses, lawmakers have legislated many interventions designed to limit the supply of prescription opioids to those who would abuse them while preserving access for legitimate users. Among these policies are prescription drug monitoring programs (PDMPs); statewide systems that record patient controlled substance prescription histories into an online database accessible to prescribers. Using PDMPs, doctors can identify patients who receive many overlapping prescriptions from several prescribers, a practice called "doctor shopping." The "non-mandated" PDMPs were available to prescribers but did not legally require doctors to query them. A number of states later pass additional usage mandates (referred to as "Mandates" from here on) to existing PDMPs, which require practitioners to query the PDMPs in certain circumstances. This paper focuses primarily on the effects of PDMPs in general, and controls for mandates. [2]

Heroin is an inexpensive, chemically similar substitute for prescription opioid painkillers. When opioid-addicted patients face additional obstacles in obtaining prescription opioids, they may initiate heroin use. Heroin transition and substitution is an important secondary-effect of supply-side interventions for policymakers to consider because in recent years heroin is often laced with fentanyl, a powerful synthetic opioid which is the cause of many unexpected overdoses (Gladden, 2016). This paper examines the effect of the PDMPs on prescription opioids, disaggregating by dosage strength of pill and examines heroin transition caused by the PDMPs measured by heroin crime rates. I exploit staggered timing of PDMP imple-

[1] National Survey on Drug Use and Health: Summary of National Findings. Substance Abuse and Mental Health Services Administration 2013.

[2] Much of the recent PDMP literature– Buchmueller and Carey (2017), Dave et al. (2017), Deza and Horn (2017), Meinhofer (2017)– focuses on usage mandates.

mentation across states in a difference-in-differences framework to identify causal effects of the programs on prescription and heroin crime outcomes.

This paper contributes to the literature on opioid supply-side interventions by showing that PDMPs have large, significant effects on heavy opioid-abusers. I accomplish this by using more disaggregated data than has yet been used in the PDMP literature, which allows me to identify heterogeneous effects of the PDMPs on the dimension of dosage strength of opioid pill and on the dimension of finer geographic detail on heroin outcomes. This paper is also unique because it is one of only a few papers that studies opioid policy effects within the abuse-prone Medicaid population. First, I provide evidence that PDMPs significantly decrease access to prescription opioids, especially within the Medicaid population. Past work has shown that PDMPs reduce prescription oxycodone, but this paper is the first to disaggregate prescription opioids by dosage of pill. I find that PDMPs decrease oxycodone in the Medicaid population by 36% within the implementing states, which is driven by a 38% decrease in oxycodone in the form of high-dose pills. Secondly, I show that heroin abuse, as measured by heroin crime rates, increases significantly due to the PDMP in counties with high rates of opioids per capita. While PDMPs don't have significant effects on heroin crime rates in the aggregate, they increase the rate of heroin crime incidents by 49-89% in counties within the top 10% of oxycodone per capita.

2 Background

Opioids are a class of natural and synthetic morphine-like drugs and include opium, morphine, oxycodone, hydrocodone, fentanyl, and heroin. The most common prescription opioids are oxycodone (the active ingredient in Percocet, OxyContin, and MS Contin) and hydrocodone (the active ingredient in Vicodin and Lortab).[3]

[3]Oxycodone and hydrocodone make up the bulk of all opioid shipments in DEA's Automation of Reports and Consolidated Orders System (ARCOS) dataset, which tracks the universe of opioid shipments. Oxycodone and hydrocodone also have the highest reported rates of abuse within the NSDUH.

2.1 History of the Opioid Crisis

The opioid crisis is commonly explained by increased access to prescription painkillers, beginning with the dramatic rise of Purdue Pharmaceutical's OxyContin in the mid-1990s. OxyContin was marketed aggressively to prescribers as safe and non-habit-forming due to its slow-release mechanism. By the early 2000s, the medical field considered pain"the 5th vital sign," asking patients to rate their pain on a scale of one to ten after taking their blood pressure, temperature, breathing and pulse.[4] With a rise in demand for opioids and doctors' increased willingness to prescribe these drugs, prescriptions for opioid pain killers increased as well. In 2012, 217 million opioid prescriptions were written in the US–a 150% increase from 1995.

2.2 Prescription Drug Monitoring Programs, Mandates, and Pill Mill Bills

As of 2017, 50 states have implemented PDMPs that track patients' prescription histories of controlled substances. Some states have tracked such histories for decades on paper, often for use by law enforcement agencies, but this paper focuses on the establishment of online, electronic drug histories that can be easily accessed by doctors. States set up online databases between 2004 and 2016, and Table 1 shows the precise dates when states allowed prescriber access.

Due to low prescriber use of the PDMPs, 12 states[5] implemented usage mandates on top of existing non-mandated PDMPs that require prescribers to query the PDMPs under certain circumstances. In addition, eight states[6] have passed packages of laws designed to stop over-prescribing at unscrupulous "pill mills": pain clinics that are typically cash-only and both prescribe and dispense opioid pills on site. These "Pill Mill Bills" often include requirements that prescribers of painkillers register with state Departments of Health, licensing requirements for pain clinics, or restrictions on in-office dispensing of painkillers.[7]

[4] In 2001 the Joint Commission on Accreditation of Healthcare Organizations added the pain scale.

[5] Delaware, Indiana, Kentucky, Louisiana, Maryland, Nevada, New Mexico, New York, Ohio Tennessee, Vermont, and West Virginia

[6] Florida, Kentucky, Louisiana, Mississippi, Ohio, Tennessee, Texas, and West Virginia

[7] For an excellent study on the Florida pill mill crackdown, see Meinhofer (2016).

I control for the usage mandates and "Pill Mill Bills" in all of my models. Table 1 displays dates of the usage mandates and "Pill Mill Bills." There is not evidence to suggest that states systematically implement both a PDMP and another policy like a Mandate or "Pill Mill Bill" in the same quarter.

2.3 Substitution to Heroin

Heroin and opioids are nearly identical at the chemical level[8] and produce similar effects in the body, acting as powerful pain suppressants and creating feelings of wellbeing and euphoria in large doses. Since many prescription opioid users previously crushed and snorted or smoked oxycodone pills to get high, smoking or snorting heroin is an easy transition (Frank, 1999; Hines et al., 2017). This transition from opioids to heroin is widely documented in small-scale research samples and surveys in the health and addiction literature (Lankenau et al., 2012; Siegal et al., 2003), and wide-scale empirical studies linking prescription opioids and heroin have just recently emerged (Alpert et al., 2017; Evans et al., 2018; Kilby, 2015; Meinhofer, 2017), with strong causal associations discovered between the OxyContin reformulation and heroin overdoses. This paper is unique among these in that I link non-mandated PDMPs to heroin transition, use heroin crime rates as a measure of heroin abuse, and perform my heroin analysis at the county level with an emphasis on heterogeneous effects.

2.4 Related Literature

Existing studies in the health literature draw varying conclusions regarding the efficacy of PDMPs, with studies finding zero effects as often as significant reductions in opioid abuse measures. However, one typically corroborated result is that PDMPs decrease prescription oxycodone shipments (Kilby, 2015; Paulozzi et al., 2011; Reisman et al., 2009; Simeone and Holland, 2006). Several authors find PDMPs without mandates affect Schedule II opioids (oxycodone) and not Schedule III-V opioids (hydrocodone).[9] Few studies that examine the

[8]Different opioids have real chemical differences but have similar effects in the body, binding to the same mu-opioid receptors (Drewes et al., 2013).

[9]Drugs receive a Schedule I-V rating based on medical usefulness and possibility of dependence, with higher numbers meaning more benign and lower numbers more dangerous. Illicit drugs like heroin and cocaine are Schedule I with little medical benefit and high potential for abuse. Some opiate painkillers

effect of the initial implementation of PDMPs use detailed prescription data, and most use aggregated opiate shipments tracked by the DEA. One exception is Kilby (2015), who uses a dataset of prescription claims from Truven Health Analytics that covers 59% of the U.S. population. She finds that non-mandated PDMPs cause a 10% reduction in oxycodone prescriptions, and also finds a 10% decrease in oxycodone shipments from the DEA's ARCOS dataset, which tracks aggregate shipments of opioids. Buchmueller and Carey (2017) utilize a claims-level subsample of the universe of Medicare claims, and find no effect of non-mandated PDMPs on abuse outcomes, perhaps because those 65 and up exhibit lower rates of opioid abuse than the younger general population.

Results for the effect of non-mandated PDMPs on outcomes outside of prescription oxycodone are mixed. Some studies find a reduction in overdoses or poisonings in response to PDMPs (Patrick et al., 2016; Reifler et al., 2012; Simoni-Wastila and Qian, 2012), whereas other studies find no response in opioid abuse outcomes. (Brady et al., 2014; Buchmueller and Carey, 2017; Dave et al., 2017; Bachhuber et al., 2016; Meara et al., 2016; Paulozzi et al., 2011)). Deza and Horn (2017) find that non-mandated PDMPs established between 2007 and 2012 reduce crime rates.[10] Because recent papers often find weak effects of non-mandated PDMPs, the opioid literature in economics has turned its' attention to PDMP mandates that require doctors to access already-established PDMPs (Buchmueller and Carey, 2017; Dave et al., 2017; Deza and Horn, 2017; Meinhofer, 2017). Mandates are effective at reducing many abuse outcomes, including doctor shopping through Medicare, substance abuse facility admissions, crime rates and fatal drug overdoses.

The economics literature has also begun to connect opioid abuse and heroin-substitution outcomes. Studies by Alpert et al. (2017) and Evans et al. (2018) examine heroin substitution in response to the 2010 reformulation of OxyContin. The reformulation made OxyContin more difficult to crush, which is a primary step to snorting, smoking, or injecting it to obtain a more intense high. Both sets of authors find dramatic increases in heroin overdose deaths in

(fentanyl, oxycodone, morphine) are Schedule II; hydrocodone was Schedule III in the time period relevant to this paper. Schedule III drug prescriptions can be refilled without making an appointment with a doctor; Schedule II drugs cannot be refilled.

[10]Deza and Horn (2017) finds the effects of PDMPs and their Mandates on crime rates, with an emphasis on violent crime and property crime. My paper focuses on drug crime, namely incidents involving the seizure of heroin or diverted opioids.

the most opioid-dense states consistent with the timing of the reformulation. In the PDMP literature, Kilby (2015), Meinhofer (2017), and Radakrishnan (2014) have studied the effect of PDMPs on heroin overdoses and treatment admissions. All three studies find limited effects of the non-mandated PDMP on heroin abuse outcomes, but do not account for the possibility of heterogeneous effects within the population.

In contrast to other PDMP papers that focus on effects of the added mandates, I focus on non-mandated PDMPs among high-abuse populations and geographical areas, and I find evidence that suggests that non-mandated PDMPs have large effects among high-abuse populations. In this paper I examine prescription outcomes in the Medicaid population, whereas other papers have focused on the general population or Medicare populations.[11] The CDC has long stated that the Medicaid population is at higher risk for opioid abuse disorders, and this paper is among the first to focus on Medicaid prescription outcomes in response to the PDMP. Past studies have shown that doctors who have patients from high-abuse populations access and query non-mandated PDMP databases at higher rates (Goodin et al., 2012; Irvine et al., 2014; Ross-Degnan et al., 2004), and my results suggest these PDMPs have effects of a similar magnitude to mandated PDMPs among the Medicaid population.

This paper also contributes to the recent economics literature covering opioid-to-heroin substitution, by treating PDMPs as a source of exogenous variation in abusers' access to prescription opioids. Other studies estimate heroin use by admissions to substance abuse treatment facilities or by death rates from heroin. I use a more detailed and informative measure, namely an incident-level dataset of reported crimes, aggregated by county and month, to measure the effects of PDMPs on heroin crime rates. Since other recent studies only found weak or inconsistent links with heroin outcomes, I use more granular geographic data to examine heterogeneous effects across counties, using the counties' levels of pre-policy opioid abuse, proxied by oxycodone milligrams per capita. To the extent that residents in more opioid-dense counties are more likely to be heavy opioid users, an increase in heroin

[11] A 2017 paper in the health policy literature by Wen et al. uses the same Medicaid dataset, using years 2011-2014. The authors do not include robustness checks or test different specification strategies of their difference-in-differences approach, nor do they provide evidence that parallel trends is supported. It is not clear if standard errors were cluster-bootstrapped, which is likely necessary due to few states implementing PDMPs between 2011 and 2014.

crime within these counties would suggest that PDMPs are highly influential in the transition to heroin use by those who heavily abuse prescription opioids.

2.5 Predictions of Policy Effects

PDMPs act as a negative supply shock for legally-obtained prescription opioids by making it more difficult for abusers to obtain prescriptions. Former doctor-shoppers may turn to the black market for diverted opioid prescriptions[12] because illegally diverted opioids are a substitute for legally prescribed opioids. The PDMP should therefore cause an increase in demand for diverted illegally-obtained opioids. However, the supply of diverted opioids available for purchase on the black market should also be affected by the PDMP because much of the supply of diverted opioids is obtained by doctor shopping, which the PDMP targets. Since the PDMP causes a decrease in supply as well as an increase in demand in the black market for illegally-diverted opioids, quantity effects are ambiguous and it is not clear whether police will encounter fewer or more illegal opioid crime incidents.

Heavy abusers who rely on doctor shopping to obtain their prescription opioids may turn to another substitute, heroin, in response to the additional obstacles to prescriptions posed by the PDMP. An increase in demand for heroin should mean police encounter more incidents where heroin is involved after the PDMP is passed.

3 Data

3.1 PDMP Dates

Table 1 shows months that states allowed prescriber access to online PDMPs. The dates were obtained from the Prescription Drug Abuse Policy System (PDAPS). There is conflicting information on the initial dates for which PDMPs are available via web access from the PDAPS, the National Alliance for Model State Drug Laws, and many other sources available online. I have chosen to use the PDAPS for the main tables in this paper in order to be

[12] In the NIBRS, an opioid is considered illegal or "diverted" when the individual in possession of the opioid does not possess a prescription.

consistent with other papers in the literature, however my results are robust to using different sets of dates.

3.2 Prescription Data: Medicaid State Drug Utilization Data

Table 2 lists summary statistics on frequency of prescription opioid and heroin abuse from self reports in the National Survey on Drug Use and Health 1990-2014. The purpose of this table is to demonstrate that 1.) the Medicaid population has higher rates of opioid abuse than the non-Medicaid population and 2.) there exist different severities of opioid abusers. The table's columns are sorted in such a way to capture ascending severity of opioid abuse: the general population of the survey, followed by respondents who have reported abusing hydrocodone, oxycodone and OxyContin. Hydrocodone is a relatively weak opioid and comes in mainly low-dose pills. Oxycodone is scheduled by the DEA as an opioid relatively more prone to abuse, and OxyContin is slow-release oxycodone in large doses. Those who abuse oxycodone and OxyContin report more frequent opioid abuse and are more likely to report having abused heroin.

The Centers for Medicare and Medicaid Services tracks the universe of prescriptions paid for at least partially by Medicaid and provides publicly available datasets that list counts of pills and prescriptions by National Drug Code (NDC), state and quarter in the Medicaid State Drug Utilization Data. The NDC is a unique drug identifier which I use to classify pill counts of opioids by drug type and dosage strength. For my analysis, I restrict my observations to tablets[13] of oxycodone and hydrocodone painkillers, the most commonly abused opioids.[14]

[13]Tablets account for 79% of the NDCs in the opioid prescription dataset, and 69% of all quantities of opioids given out. In addition to tablets, opioids come as solutions, syrup, and patches, mostly in the form of codeine, a relatively weak form of opioid.

[14]Oxycodone and hydrocodone are the most commonly abused opioids (NSDUH) and the only opioids the Drug Enforcement Administration has tracked for the entire time period between 2000 and 2015. There is not evidence that PDMPs affect other less-commonly abused opioids like oxymorphone, hydromorphone, meperidine, tramadol, tapentadol, morphine, or methadone. The unresponsiveness of the more uncommon opioids is consistent with findings in Kilby (2015). Results available upon request.

3.3 Drug Enforcement Agency ARCOS Data

The Drug Enforcement Agency tracks aggregate shipped amounts of controlled substances through the Automation of Reports and Consolidated Orders System (ARCOS). These data are recorded by state and quarter and by zipcode and quarter. The ARCOS data provides more fine-grained geographical information at the zipcode and county levels. The ARCOS data are not at the NDC level of specificity, so I am not able to decipher dosage amounts (strong versus weak doses) nor dosage form (tablets versus solutions usually given under medical supervision) of the oxycodone and hydrocodone within the aggregate population data.

Table 3 displays Medicaid drug milligrams *in tablet form* per enrollee and ARCOS drug milligram shipments *in all forms* per population in the data. The oxycodone per capita rate from the ARCOS and the oxycodone *tablet milligrams* per Medicaid enrollee[15] from the Medicaid data appear similar at around 55 morphine units per quarter per person, which is approximately 6-8 low dose pills or 1-2 high-dose pills per capita. In the Medicaid data, where oxycodone can be broken down into high dose (> 10 mg) and low dose (≤ 10 mg), the bulk of prescribed oxycodone is dispensed in high dosage tablet form. Hydrocodone comes in nearly exclusively low-dose tablets, often in combination with acetaminophen, as is the case with brand name Vicodin. It is unknown wheter the proportions of weak dose versus strong dose tablets of oxycodone (or hydrocodone) in the Medciaid data is the same as in the general population because the ARCOS data lacks this information. I assume the Medicaid information is representative and explore it because policy effects on dosage strength are an interesting and potentially important contribution to the literature on opioid supply-side interventions.

3.4 NIBRS

The National Incident-Based Reporting System (NIBRS)[16] is an incident-level dataset of crimes committed in participating jurisdictions. For the purpose of this paper, I use a

[15] I classify capsules and tablets as tablets.

[16] The NIBRS was used instead of the UCR because the UCR does not differentiate heroin from cocaine crimes in its counts of drug offenses.

complete monthly panel of 735 counties in 26 states from 2004-2014. A map of the 735 counties is documented in Figure 1, which shows that coverage is nationally widespread, including some states with near-complete coverage. The NIBRS is a more-detailed subset of the FBI's Uniform Crime Reporting (UCR) system, and the 2004 NIBRS covered police districts in areas containing 20% of the United States population and accounted for 16% of the UCR crime statistics data collected by the FBI. Reported crimes include information about the location where the incident occurred, details about the nature of the crime, and demographic characteristics of the offender (among other information).

For my analysis, I focus on incidents involving the seizure of heroin or illegally obtained prescription opiates. Outcomes are in number of crimes per 100,000 population per month in each covered county. Dependent variables include incidents where heroin or opiates are seized, and incidents involving possible drug dealers, as defined below.

I divide counties based on oxycodone milligrams per capita from the ARCOS data, for the year 2004–late enough that the opioid crisis was beginning to affect counties differently, but early enough that most PDMPs had not been implemented. My rationale is that PDMPs should have a larger impact and cause more opioid abusers to transition to heroin in areas with a larger stock of opioid abusers prior to the PDMP. The distribution of oxycodone density across different counties is plotted in Figure 2. Most counties receive 10-50 milligrams per person in oxycodone shipments, but the figure suggests that there are "outlier" counties that receive many more opioids per capita. I split the counties on the 90th percentile[17] of oxycodone density, at 63.15 milligrams of oxycodone per capita. The top 10% and bottom 90% of counties by oxycodone milligrams per capita are defined as high" and low oxycodone density counties, respectively. Figure 1 displays a color gradient corresponding to each county's oxycodone density, with the most oxycodone dense counties appearing in New England, the Appalachian regions of Tennessee, Virginia, and West Virginia, and a few counties in Ohio, which are all known to be high-abuse areas.

Table 4 displays summary statistics of drug crimes from the NIBRS data. The table is split into 3 panels: crime rates across all 735 counties in the NIBRS, crime rates within low oxycodone-density counties, and crime rates high oxycodone-density counties. The typical

[17]Results are robust to using other cutoffs.

county realizes 1.3 heroin incidents and 2.2 incidents of illegally diverted opioids per 100,000 population per month, and high-oxycodone counties experience twice as many heroin and opioid incidents (about 2 and 4 per 100,000 population per month) than low-oxycodone counties (1 and 2 incidents per 100,000 population per month).

To identify possible heroin dealers and opiate dealers in the NIBRS dataset, I count the individuals per county and month who are selling heroin/opiates, or are carrying large amounts of heroin or opiates, often in combination with large amounts of other drugs as well. In Table 4, the average county realizes 0.502 incidents per month involving possible heroin dealers, and 0.523 involving possible dealers of diverted opioids. The low oxycodone counties experience about 0.4 incidents of each type per month, whereas the high oxycodone counties experience about 1 heroin and diverted-opioid incidents per month which involve a possible dealer. Again, the crime ratio for the two sets of counties is about two to one.

4 Empirical Methods

For the main analysis of this paper, I use a difference-in-differences regression framework on a state-quarter panel and a county-month panel weighted by population, using the different implementation dates by state of PDMPs, Mandates and Pill Mill Bills as a source of exogenous variation in treatment. The identifying assumption of the difference-in-differences specification is the parallel trends assumption that treated and untreated states follow similar growth paths prior to the treatment and would have continued to do so in the absence of treatment. I adapt the difference-in-differences models into an event-study framework with policy lags and leads to provide visual evidence of the policies' effects. I also supplement the analysis with interactive fixed effects factor models (IFE), as detailed in Bai (2009), which are explained in Appendix Appendix C.

4.1 The Effect of PDMPs on Prescription Data and ARCOS Shipments

Models for finding the effect of the policies on the amount of opioids used by Medicaid recipients and ARCOS shipments are at the state and quarter level. The model is as follows:

$$RxOutcome_{it} = \alpha + \beta PDMP_{it} + \eta Mandate_{it} + \phi PillMillBill_{it} + \Psi X_{it} + \iota_i + \gamma_t + \epsilon_{it}$$

Where $RxOutcome_{it}$ is logged milligrams of Medicaid oxycodone or hydrocodone per Medicaid enrollee, or logged total ARCOS shipped amounts of oxycodone or hydrocodone per population in state i in quarter t or earlier.[18] $PDMP_{it}$, $Mandate_{it}$ and $PillMillBill_{it}$ are indicators that are equal to one if state i has established an electronic Prescription Drug Monitoring Program, Mandate or Pill Mill Bill by quarter t. [19] γ_t is a set of time period fixed effects and ι_i is a set of geography fixed effects that control for time-invariant characteristics. ϵ_{it} is a stochastic, normally distributed error term.

Event-study graphs (for example, graphs in Figures 3 and 4) are based on the following models:

$$RxOutcome_{it} = \alpha + \Sigma_{p=-5}^{10} \beta_p PDMP_{i,t+p} + \eta Mandate_{it} + \phi PillMillBill_{it} + \Psi X_{it} + \iota_i + \gamma_t + \epsilon_{it}$$

$PDMP_{i,t+p}$ is an indicator equal to one if the policy started in state i in the time $t+p$. The coefficients β_p capture the measured effect of the PDMP at p periods after passage. For example, if $p = 2$, $\beta_{i,t+2}$ would capture the effect of the policy on the outcome variable 2 periods after passage.[20] Negative values of p correspond to "leads," which capture the effect of the policy before it is implemented and should be zero under the parallel trends

[18] Logged linear models are used for prescription outcomes, but results on Medicaid oxycodone, strong Medicaid oxycodone, and ARCOS oxycodone are robust to the removal of the log and are available upon request. Prescription results are also robust under a Poisson model, also available upon request to the author.

[19] A state with more than one policy, like Kentucky, which has a PDMP, a usage mandate, and a pill mill crackdown by July 2012 will have all three indicator variables equal to one, with the cumulative effect of the policies on the outcome equal to the sum of the variables' coefficients.

[20] Indicator variables $PDMP_{i,t+p}$ are only equal to one in the time p period after passage, and equal zero in all other time periods.

assumption of the difference-in-differences methodology.

X_{it} is a matrix of controls that capture changes within states over time in demographic characteristics and economic characteristics. State-level controls for the prescription outcome models are summarized in Appendix A. The matrix includes the fraction of the population that is black, Hispanic, or of other non-white race, as well as the poverty rate, unemployment rate, average weekly wage rate, average income per capita, and the fraction of the population employed in the agriculture or manufacturing sectors. I include controls for the age composition of the population (fraction of population in age groups 10-19, 20-29, 30-39, 40-49, 50-59, 60-69 and 70 years or older) and the gender composition of the population. I control for the average number of pills of all drug types filled through Medicaid per Medicaid enrollee to capture variation in the overall Medicaid-prescribing behavior within states over time. I also control for the implementation of Medicare Part D, which increased elderly access to prescription drugs, by controlling for the fraction of the population enrolled in Medicare interacted with an indicator that turns on in 2006, when Medicare Part D began.[21] I control for state-varying Medicaid expansions under the Affordable Care Act, including early adopting states.

Finally, I control for effects of the abuse-deterrent reformulation of OxyContin that became prevalent in 2010, because Alpert et al. (2017) and Evans et al. (2018) find a large impact of the OxyContin reformulation on heroin overdoses. Both studies find that states react differently to the OxyContin reformulation based on their pre-policy rate of reported OxyContin abuse (in the NSDUH) (Alpert et al., 2017) and oxycodone per capita in the ARCOS (Evans et al., 2018). This is accomplished by multiplying a post-reformulation indicator variable by the pre-reformulation proxy for opioid abuse. In this paper I proxy opioid abuse by using a state's mean number of OxyContin milligrams per Medicaid enrollee (in the Medicaid data) in 2004.[22]

[21] Since many opioid abusers obtain their drugs from friends and relatives, increasing senior access to prescription drugs increases opioid abuse. See Pacula, Powell and Taylor (2015) for a time-study analysis.

[22] Alpert et al. (2017) use OxyContin abuse that is reported in the NSDUH as a measurement for how states will experience the effects of the OxyContin reformulation on heroin overdoses. When I instead use OxyContin prescribing rates in the Medicaid data on heroin crime outcomes, my result magnitudes are similar to the Alpert et al. (2017) effects of NSDUH OxyContin abuse reporting on heroin overdoses.

4.2 The Effect of the PDMPs on Crime Rates

Crime-rate models use the NIBRS panel data at the county and month level. The main analytic-weighted difference-in-differences models are in the form:

$$CrimeRate_{ct} = \alpha + \beta PDMP_{ct} + \eta Mandate_{ct} + \phi PillMillBill_{ct} + \Psi X_{ct} + \iota_c + \gamma_t + \epsilon_{ct}$$

$CrimeRate_{ct}$ is the number of crimes per 100,000 people in the NIBRS-covered population in county c in month t.[23] $PDMP_{ct}$, $Mandate_{ct}$, and $PillMillBill_{ct}$ are indicators equal to one if the PDMP, Mandate, or menu of "Pill Mill" legislation is in effect in county c's state in month t, and β, η, and ϕ capture the effect of the policies on the outcome crime-rate. X_{ct} is a matrix of county characteristics that vary over time, and γ_t and ι_c are time and county fixed effects.

Controls in matrix X_{ct} include racial, age, and gender demographics like in the prescription section, but instead at the county level. I also control for the county-level unemployment rate and average weekly wage. I control for the fraction of the county's labor force that works in a manufacturing job and use pharmacies per capita to control for changing access to prescription drugs. I control for law enforcement officers per capita in each crime-reporting jurisdiction over time to account for any enforcement changes within counties that may correspond to the timing of the policies. I also control for the abuse-deterrent reformulation of OxyContin and the enactment of Medicare Part D as I did for the models in the prescription opioid models.[24] I adapt the approach in Alpert et al. (2017) and Evans et al. (2018) for measuring the effect of the OxyContin reformulation to the county level by multiplying a post-August 2010 indicator by counties' pre-reformulation oxycodone density in the ARCOS data.[25] Summary statistics and data sources for county controls are listed in Appendix A.

[23] Outcomes for crime rates are not logged because 86% of county-month pairs report zero heroin incidents. Heroin results are robust under a Poisson regression model, as documented in a later section.

[24] Medicare enrollment by year is available at the state level, but not at the county level. At the county level, I instead proxy by using fraction of the population who are aged 65 and up.

[25] Medicaid data are not available at the disaggregated county level. To measure a treatment intensity of the OxyContin reformulation at the county level, I use ARCOS oxycodone shipments per capita from each county interacted with a post-August 2010 indicator. This method is almost identical to the method in Evans et al. (2018), but at the county rather than state level. My estimates of the county-level effect of the reformulation (measured by ARCOS oxycodone density) on heroin abuse (measured by heroin crime rates) are similar in magnitude to those in Alpert et al. (2017), who also find the effect of the reformulation

To identify the effect of the policies over time and support the identification assumption of parallel trends, I create graphs with coefficient estimates obtained from the event study (as seen in Figures 6):

$$CrimeRate_{ct} = \alpha + \Sigma_{f=-12}^{12} \beta_f PDMP_{i,t+f} + \eta Mandate_{ct} + \phi PillMillBill_{ct} + \Psi X_{ct} + \iota_c + \gamma_t + \epsilon_{ct}$$

β_f captures the effect of the PDMP on the crime-outcome variable at f months after passage. For example, β_5 estimates the effect of the PDMP 5 months after passage. The β_f coefficients associated with negative, (pre-policy) time periods should equal zero and will capture pre-policy effects if the parallel trends assumption is not satisfied.

5 Results

5.1 Effect of the PDMP on Prescription Amounts

Table 5 shows the estimates for the coefficients of interest in Equation 4.1, measuring the effect of the PDMP and related policies on the Medicaid prescription and ARCOS shipments of oxycodone and hydrocodone amounts per capita.[26] Columns (1)-(4) contain coefficient estimates from the weighted difference-in-differences model run on Medicaid oxycodone, weak oxycodone, strong oxycodone, and hydrocodone, respectively. Columns (5) and (6) contain the estimates from the model run on ARCOS total oxycodone and hydrocodone.

Columns (1)-(3) show the PDMP reduces Medicaid oxycodone per Medicaid enrollee. This reduction is due to both a decrease in weak and strong doses of oxycodone pills, a statistically significant 37% decrease in the amount of oxycodone dispensed through Medicaid. Figure 3 shows the accompanying event study graphs of the effect of the PDMP on Medicaid oxycodone levels. The leads all graphs are close to zero until the policy takes effect at quarter zero, showing no evidence of violation of the parallel trends assumption. The graphs show a break in trend among the treated states at the time of the policy implementation, lending

(measured by NSDUH OxyContin abuse reports) on heroin abuse (measured by heroin overdoses).

[26] The model specification in Table 5 includes state and quarter fixed effects and state controls, and weights observations and standard errors by either state Medicaid enrollees for models run on Medicaid outcomes (Columns (1)-(4)) or state population for models run on ARCOS data (Columns (5) and (6)).

evidence to the PDMP causing a decrease in oxycodone.

In Column (5), the PDMP is found to reduce the aggregate amount of oxycodone shipped per capita by 10%, significant at the 5% level. Neither Columns (4) nor (6) suggest that the PDMP has an effect on hydrocodone use. Figure 4 plots the event study coefficient of the model on aggregate shipment rates of oxycodone from the ARCOS data, and shows a reduction among such shipments per capita over time. This result is consistent with much of the PDMP literature that uses ARCOS data as an outcome response to the systems, including Kilby (2015), who also finds a 10% reduction in ARCOS oxycodone in response to the non-mandated PDMP. I find larger oxycodone reductions for the Medicaid population than for the aggregate population, which can be explained by several reasons. Medicaid enrollees report higher rates of opioid and heroin abuse (Frank, 1999), and prescribers who interact with high-abuse populations are more likely to check the PDMP (Goodin et al., 2012; Ross-Degnan et al., 2004; Irvine et al., 2014). In short, the Medicaid population may be specially positioned for the PDMP to work well on it.

Although many of the models in Table 5 show significant effects of the Mandate and Pill Mill Bill policies on drug amounts, many of the event study models fail the parallel trends assumption and the effects of the policies are not clear. Both Mandate and Pill Mill Bill results on prescription outcomes are volatile across model specifications, and are not discussed.

A novel contribution of this study is that I find the decrease Medicaid-prescribed oxycodone is driven by reductions in prescriptions in high dose (>10mg) and low dose ($\leq$10mg) pills, but the effect is more pronounced among high dose pills. No other study has considered heterogeneous effects of the PDMP on oxycodone drugs of differing strengths. Figure 5 displays coefficient estimates of the effect of the PDMP on the rate of Medicaid pills dispensed, disaggregated by oxycodone strength of pill by milligrams per pill. I find that reductions in the 10, 30, 40, and 80 milligram pills are driving the overall reduction in oxycodone prescriptions. I also find that PDMP reductions among Medicaid prescriptions are only prevalent among generic oxycodone pills, and not brand-name OxyContin.[27]

[27]This is comparable to results from Hwang et al. (2015) and Meinhofer (2016), who find that only generic oxycodone is responsive to the reformulation of OxyContin and Florida's crackdown on pill mills, respectively. Additional results on brand-name versus generic oxycodone are available upon request to the author.

5.2 Effect of the PDMP on Drug Crime Rates

Table D7 shows the effect of the PDMP on crime incidents in which heroin is seized. The rate of heroin incidents in this table are in incidents per 100,000 NIBRS-covered population in a county and month. The table is broken up into three panels, for models run on A.) all 735 counties, B.) on the bottom 90% of counties by oxycodone density, and C.) on the top 10% of counties by oxycodone density (all as determined from the ARCOS dataset). Columns display coefficient estimates from difference-in-difference models with fixed effects in Column (1), adding controls to the model in Column (2), and linear time trends to Column (3). Column (4) contains estimates from the IFE Factor model specification which more efficiently controls for county-specific curvature in time trends that is independent from the policies.

Among all counties and counties with a lower measurement of oxycodone density, the PDMP is not shown to have a large of significant effect. However, counties with a relatively higher measurement of pre-policy oxycodone milligrams per capita (in Panel C) are shown to experience higher rates of offenders carrying heroin after the passage of the PDMP. Depending on model specification, the PDMP is increasing heroin incidents by 1.1-2.1 additional incidents per 100,000 population per month, a 49-89% increase from these counties' baseline level of 2.3 incidents per 100,000 population each month. The result is robust to a vast array of different model specifications and differing PDMP date sources, consistently showing the PDMP causes 1-2 additional heroin incidents per 100,000 population per month within the most oxycodone dense counties.

Figure 6 shows the effect over time of the PDMP on the rate of heroin incidents across county types and model specifications. Consistent with Panels A and C of Table D7, the graphs show increases in heroin incidents after the implementation of the PDMP. The leads on the graphs are close to zero, and support the identifying assumption of the differences-in-differences model that states that treated counties are trending similarly to untreated counties prior to the policy. Graphical depictions of the effect of the PDMP within oxycodone-dense counties show an additional 1-1.5 heroin incidents per 100,000 population per month consistent with the timing of the policies, or an approximate 49-89% increase in the rate.

Table 7 contains estimated effects of the PDMP on several different drug-crime outcomes, split on high and low oxycodone density. This table contains results from the difference-in-differences model specification without county-specific linear time trends (the "Controls" model from Table D7). Again, Panels A-C distinguish types of counties by oxycodone density. Columns (1) through (4) document model coefficient estimates on the rates of heroin incidents (taken from Table D7), incidents that involved possible heroin dealers (Column (2)), diverted opiate incidents (Column (3)), and incidents involving possible dealers of diverted opiates (Column (4)).

Panel C shows that in the most oxycodone-dense counties, the incidents with possible heroin dealers increase significantly: 0.324 additional incidents per 100,000 population after the PDMP, equal to a 36% increase from the pre-policy, pre-announcement level of 0.902. Figure 7 displays event studies of the PDMP effect on possible heroin dealers in all counties and in the most oxycodone-dense counties. There is a significant increase in possible heroin dealers in the most opioid-dense counties, but not across all counties.[28]

A crime involving diverted opioids is an incident in the NIBRS in which an offender is carrying prescription opioids for which he or she does not have a prescription. The PDMP's effect on opiate incidents is noisy and has large standard errors, consistent with predictions. It remains noisy and insignificant, usually with point estimates near zero, across different model specifications. Close examination of event study graphs of opiate incidents over time do not reveal consistent effects or anything of note for all counties or for the more oxycodone-dense counties. Figure 8 shows such graphs.[29] Regardless of the model used, the PDMP does not produce significant effects on the rate of diverted opioid incidents. Results on possible opioid dealers are similarly noisy, insignificant, near zero and are not discussed.

Theory predicts an increase in demand for heroin and quantity traded of heroin, because heroin is a substitute for prescription opioids. I find a significant 40%-60% increase in heroin incidents in the most susceptible areas, equal to about 1-2 additional incidents per 100,000

[28] As shown in Panel C of Table D7, the effect of the PDMP on heroin outcomes is driven by those counties in the top half of the oxycodone-per-capita distribution.

[29] The plotted coefficient points come from the IFE factor model this time because the difference-in-differences event studies do not satisfy the parallel trends identification assumption, even when accounting for linear county-specific time trends. That is, the linear time trends are not enough to capture trends in illegal opioid seizures in the data.

population per month, consistent with predictions. Simple theory predicts PDMPs cause an increase in the demand for illegal prescription opiates, but a decrease in supply of illegal prescription opiates (diverted from the market of legal prescription opiates). These opposing market forces lead to a predicted increase in the street price of prescription opioids, but ambiguous effects on the predicted quantity traded. These imprecise, zero estimates of the effect of the PDMP on opiate incidents are not surprising in light of the uncertain theoretical predictions.

Graphical Evidence of the Effect of the Mandated PDMP and Pill Mill Bills on Drug Crimes Figures 9 and 10 display the estimated effects of the Mandated PDMP and Pill Mill Bill on heroin incidents and illegal opioid incidents. There is some evidence that the Mandated PDMP causes a decrease in illegal opioid incidents in the most opioid-dense counties, but there is not evidence that the Mandate has an effect on opioid incidents nor heroin incidents in the typical NIBRS county. The Pill Mill Bill appears to decrease the rate of heroin incidents among the most opioid-dense counties, but doesn't have a clear effect on opioid incidents nor heroin incidents in the average NIBRS county. Due to limited coverage of the NIBRS, the Mandate drug results are identified off of changes in 175 counties in 8 states (or 53 counties in 6 states with high oxycodone-density counties), and the Pill Mill Bill drug results are identified off of changes in 159 counties in 6 states (or 44 counties in 3 states with high-oxycodone density counties). The results are robust to the Wild Cluster Bootstrap procedure covered in Cameron et al. (2008), but results may not generalize to the typical county or state. Additional states are adding provider-access Mandates to their existing PDMPs and are passing additional Pill Mill crackdown legislation, but recent changes are beyond the time coverage of the data used in this study. Additional studies in the future may clarify the effect of the Mandate and Pill Mill Bill policies on drug substitution.

6 Conclusion

Opioids are highly addictive and foster dependence among individuals taking high doses. When abusers' supply of prescription opioids is cut off, some may turn to heroin or illegally

diverted opioids to avoid the undesirable physical symptoms of opioid withdrawal.

Every state established electronic prescription drug monitoring programs between 2004 and 2017 to limit prescribing of opioids to those with patterns of abuse. Nationwide, PDMPs cause an 8% reduction in prescription oxycodone quantities, and an 11% increase in heroin crime, although this result is statistically insignificant. Prescription monitoring has larger effects on prescriptions in the Medicaid population and causes a statistically signficant 24% reduction in oxycodone prescribed, which is driven by an even larger 35% decrease in high-dosage pills. Heroin crime results are driven by the counties that have the highest pre-PDMP oxycodone per capita, which is consistent with substitution to heroin in response to the policy. The PDMP causes a 40% to 60% increase in heroin incidents within the most oxycodone-dense counties.

This paper contributes to the literature on the effects of legislation that reduces the supply of opioids, and finds evidence of substitution behavior in response to PDMPs. The results show heterogeneous effects of PDMPs within state populations, a possible explanation for the mixed, often statistically insignificant results in the PDMP literature. When focusing on the high abuse Medicaid enrollee subsection of the population and disaggregating oxycodone by pill strength, evidence here supports that PDMPs successfully limit the supply of opioids to the heaviest abusers.

Disaggregating Medicaid data on drug level allows me to identify heterogeneous policy effects on drugs with differing amounts of oxycodone. Using county-month level crime data, I am able to find heterogeneity of PDMP effectiveness within state populations. Disaggregating outcomes to the county level allows for a better examination of high-abuse populations, because of differences in opioid abuse across counties within states.

The opioid epidemic costs the U.S. an estimated $78.5 billion annually. Policymakers have primarily used supply-side policy levers in attempts to reduce the flow of new opioid addicts. However, supply-side policies haven't properly accounted for substitution responses among the stock of existing opioid-dependent individuals. Future supply-side interventions should provide alternative options for those already in the throes of addiction, or simultaneously target alternate sources of opioids.

References

Alpert, A., D. Powell, and R. L. Pacula (2017). Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids. Technical report, National Bureau of Economic Research.

Bachhuber, M. A., B. C. Maughan, N. Mitra, J. Feingold, and J. L. Starrels (2016). Prescription monitoring programs and emergency department visits involving benzodiazepine misuse: early evidence from 11 united states metropolitan areas. *International Journal of Drug Policy 28*, 120–123.

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica 77*(4), 1229–1279.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica 70*(1), 191–221.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics 119*(1), 249–275.

Brady, J. E., H. Wunsch, C. DiMaggio, B. H. Lang, J. Giglio, and G. Li (2014). Prescription drug monitoring and dispensing of prescription opioids. *Public Health Reports 129*(2), 139–147.

Buchmueller, T. C. and C. Carey (2017). The effect of prescription drug monitoring programs on opioid utilization in medicare. Technical report, National Bureau of Economic Research.

Cameron, A. C., J. B. Gelbach, and D. L. Miller (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics 90*(3), 414–427.

Case, A. and A. Deaton (2015). Rising morbidity and mortality in midlife among white non-hispanic americans in the 21st century. *Proceedings of the National Academy of Sciences 112*(49), 15078–15083.

Dave, D. M., A. M. Grecu, and H. Saffer (2017). Mandatory access prescription drug monitoring programs and prescription drug abuse. Technical report, National Bureau of Economic Research.

Deza, M. and B. P. Horn (2017). The effect of prescription drug monitoring programs on crime. *Working Paper*.

Drewes, A. M., R. D. Jensen, L. M. Nielsen, J. Droney, L. L. Christrup, L. Arendt-Nielsen, J. Riley, and A. Dahan (2013). Differences between opioids: pharmacological, experimental, clinical and economical perspectives. *British journal of clinical pharmacology 75*(1), 60–78.

Evans, W. N., E. Lieber, and P. Power (2018). How the reformulation of oxycontin ignited the heroin epidemic. *National Bureau of Economic Research*.

Frank, B. (1999). An overview of heroin trends in new york city: past, present and future. *The Mount Sinai journal of medicine, New York 67*(5-6), 340–346.

Gladden, R. M. (2016). Fentanyl law enforcement submissions and increases in synthetic opioid–involved overdose deaths—27 states, 2013–2014. *MMWR. Morbidity and mortality weekly report 65*.

Goodin, A., K. Blumenschein, P. R. Freeman, and J. Talbert (2012). Consumer/patient encounters with prescription drug monitoring programs: Evidence from a medicaid population. *Pain physician 15*(3 Suppl), ES169.

Hines, L. A., M. Lynskey, K. I. Morley, P. Griffiths, M. Gossop, B. Powis, and J. Strang (2017). The relationship between initial route of heroin administration and speed of transition to daily heroin use. *Drug and Alcohol Review*.

Hwang, C. S., H.-Y. Chang, and G. C. Alexander (2015). Impact of abuse-deterrent oxycontin on prescription opioid utilization. *Pharmacoepidemiology and drug safety 24*(2), 197–204.

Irvine, J. M., S. E. Hallvik, C. Hildebran, M. Marino, T. Beran, and R. A. Deyo (2014). Who uses a prescription drug monitoring program and how? insights from a statewide survey of oregon clinicians. *The Journal of Pain 15*(7), 747–755.

Kilby, A. (2015). Opioids for the masses: welfare tradeoffs in the regulation of narcotic pain medications. *Cambridge: Massachusetts Institute of Technology*.

Lankenau, S. E., M. Teti, K. Silva, J. J. Bloom, A. Harocopos, and M. Treese (2012). Initiation into prescription opioid misuse amongst young injection drug users. *International Journal of Drug Policy 23*(1), 37–44.

Meara, E., J. R. Horwitz, W. Powell, L. McClelland, W. Zhou, A. J. O'malley, and N. E. Morden (2016). State legal restrictions and prescription-opioid use among disabled adults. *New England Journal of Medicine 375*(1), 44–53.

Meinhofer, A. (2016). The war on drugs: Estimating the effect of prescription drug supply-side interventions.

Meinhofer, A. (2017). Prescription drug monitoring programs: The role of asymmetric information on drug availability and abuse. *American Journal of Health Economics*.

Patrick, S. W., C. E. Fry, T. F. Jones, and M. B. Buntin (2016). Implementation of prescription drug monitoring programs associated with reductions in opioid-related death rates. *Health Affairs 35*(7), 1324–1332.

Paulozzi, L. J., E. M. Kilbourne, and H. A. Desai (2011). Prescription drug monitoring programs and death rates from drug overdose. *Pain Medicine 12*(5), 747–754.

Radakrishnan, S. (2014). The impact of information in health care markets: Prescription drug monitoring programs and abuse of opioid pain relievers. *accessed February 24*, 2016.

Reifler, L. M., D. Droz, J. E. Bailey, S. H. Schnoll, R. Fant, R. C. Dart, and B. Bucher Bartelson (2012). Do prescription monitoring programs impact state trends in opioid abuse/misuse? *Pain Medicine 13*(3), 434–442.

Reisman, R. M., P. J. Shenoy, A. J. Atherly, and C. R. Flowers (2009). Prescription opioid usage and abuse relationships: an evaluation of state prescription drug monitoring program efficacy. *Substance abuse: research and treatment 3*, 41.

Ross-Degnan, D., L. Simoni-Wastila, J. S. Brown, X. Gao, C. Mah, L. E. Cosler, T. Fanning, P. Gallagher, C. Salzman, R. I. Shader, et al. (2004). A controlled study of the effects of state surveillance on indicators of problematic and non-problematic benzodiazepine use in a medicaid population. *The International Journal of Psychiatry in Medicine 34*(2), 103–123.

Siegal, H. A., R. G. Carlson, D. R. Kenne, and M. G. Swora (2003). Probable relationship between opioid abuse and heroin use. *American family physician 67*(5), 942–945.

Simeone, R. and L. Holland (2006). *An evaluation of prescription drug monitoring programs*. US Department of Justice, Office of Justice Programs, Bureau of Justice Assistance.

Simoni-Wastila, L. and J. Qian (2012). Influence of prescription monitoring programs on analgesic utilization by an insured retiree population. *Pharmacoepidemiology and drug safety 21*(12), 1261–1268.

Table 1: Effective Dates of Electronic PDMPs, Mandates, and "Pill Mill" Legislation

State	PDMP Date	Mandate Date	"Pill Mill" Bill Date
Alabama	June 2007		
Alaska	January 2012		
Arizona	December 2008		
Arkansas	May 2013		
California			
Colorado	February 2008		
Connecticut			
Delaware	August 2012	March 2012	
Florida	October 2011		July 2011
Georgia	July 2013		
Hawaii	June 1992		
Iowa	March 2009		
Idaho	May 1999		
Illinois			
Indiana			
Kansas	April 2011		
Kentucky	July 1999	July 2012	July 2011
Louisiana	January 2009	August 2014	July 2005
Maine	January 2005		
Maryland	December 2013		
Massachusetts	December 2013	June 2013	
Michigan	January 2003		
Minnesota	April 2010		
Mississippi	January 2008		September 2011
Missouri			
Montana	October 2012		
Nebraska	April 2011		
Nevada	July 1997	October 2007	
New Hampshire	October 2014		
New Jersey	January 2012		
New Mexico	August 2005	September 2012	
New York	January 2010	August 2013	
North Carolina	October 2007		
North Dakota	September 2007		
Ohio	October 2006	November 2011	May 2011
Oklahoma			
Oregon	September 2011		
Pennsylvania			
Rhode Island	January 2005		
South Carolina	September 2008		
South Dakota	March 2012		
Tennessee	December 2006	January 2013	January 2012
Texas	January 1982		June 2009
Utah	January 1996		
Vermont	April 2009	November 2013	
Virginia	June 2006		
Washington	January 2012		
West Virginia			September 2014
Wisconsin	May 2013		
Wyoming	October 2004		

Dates obtained from the Prescription Drug Abuse Policy System (PDAPS), which keeps a list of PDMP web access dates.

Table 2: Summary Statistics on Opioid Abuse of Individuals in the NSDUH

	All Respondents	Hydrocodone Abusers	Oxycodone Abusers	OxyContin Abusers
Non-Medicaid Population				
Fraction Abused Opioids	0.077	1	1	1
Past Year Frequency Opioids	1.139	17.331	15.77	38.286
Fraction Abused Heroin	0.011	0.084	0.120	0.226
Past Year Frequency Heroin	0.116	1.685	1.965	6.091
Fraction Abused Hydrocodone	0.051	1	0.533	0.900
Fraction Abused Oxycodone	0.045	0.477	1	1
Fraction Abused OxyContin	0.011	0.189	0.234	1
Observations	915,123	70,637	51,222	17,837
Medicaid Population				
Fraction Abused Opioids	0.105	1	1	1
Past Year Frequency Opioids	2.535	26.76	26.66	51.666
Fraction Abused Heroin	0.022	0.150	0.187	0.302
Past Year Frequency Heroin	0.365	3.711	4.690	11.11
Fraction Abused Hydrocodone	0.065	1	0.621	0.898
Fraction Abused Oxycodone	0.054	0.522	1	1
Fraction Abused OxyContin	0.017	0.232	0.307	1
Observations	163,528	12,756	9,323	3,725

The table displays summary statistics from the National Survey on Drug Use and Health 1990-2014. For the Non-Medicaid and Medicaid Population, indicators for and frequency of opioid abuse are reported for all survey respondents, survey respondents who report having ever abused hydrocodone, oxycodone or OxyContin. Medicaid enrollees report higher rates of abuse than those not enrolled in Medicaid, and respondents who report abusing OxyContin and oxycodone report more frequent misuse of opioids.

Table 3: Summary Statistics of ARCOS and Medicaid Drug Amounts

	ARCOS Data		Medicaid Data	
	Morph. Units (Millions)	Morph. Units Per Capita	Morph. Units (Millions)	Morph. Units Per Capita
Oxycodone	312.5	55.54	25.90	52.24
Oxycodone: Weak Dose	–	–	9.083	17.53
Oxycodone: Strong Dose	–	–	16.81	34.71
Hydrocodone	149.4	24.68	7.377	11.44
Hydrocodone: Weak Dose	–	–	7.377	11.44
Hydrocodone: Strong Dose	–	–	–	–
Observations	5100	5100	5100	5100

Panel Data is by state and quarter. Data is in morphine-equivalent milligrams of oxycodone and hydrocodone. Strong dose pills are pills containing more than 15 morphine equivalent milligrams of the active opioid painkiller. Hydrocodone does not come in tablets containing more than 15 morphine equivalent milligrams. The ARCOS data contains information on aggregate shipped amounts of oxycodone and hydrocodone, and the Medicaid drug data contains information at the drug level, which is aggregated by strength.

Table 4: Summary Statistics of Crime Rates Per 100,000 Population

	N	Mean	Std. Error
All 735 Counties			
Heroin Incidents	93,742	1.299	2.716
Opiate Incidents	93,742	2.175	4.533
Heroin Dealer	93,742	0.502	1.290
Opiate Dealer	93,742	0.523	2.604
655 Low Oxycodone Density Counties			
Heroin Incidents	86,232	1.124	2.481
Opiate Incidents	86,232	1.866	3.792
Heroin Dealer	86,232	0.426	1.199
Opiate Dealer	86,232	0.432	2.202
80 High Oxycodone Density Counties			
Heroin Incidents	10,548	2.342	3.655
Opiate Incidents	10,548	4.009	7.300
Heroin Dealer	10,548	0.949	1.663
Opiate Dealer	10,548	1.060	4.233

Panel Data is by county and month. 735 counties across 26 states have complete monthly coverage within the NIBRS dataset during the entire period of 2004 to 2014. Only counties with full coverage are used in the crime rate analysis.

Table 5: The Effect of Policies on Logged Prescription Amounts per Capita

	Medicaid Data				ARCOS Data	
	(1)	(2)	(3)	(4)	(5)	(6)
	Oxycodone	Weak Oxycodone	Strong Oxycodone	Hydrocodone	Oxycodone	Hydrocodone
PDMP	-0.368**	-0.268**	-0.382**	-0.0581	-0.103**	0.000
	(0.157)	(0.128)	(0.173)	(0.095)	(0.049)	(0.020)
	[0.019]	[0.037]	[0.028]	[0.299]	[0.04]	[0.501]
Mandate	0.118	0.00259	0.112	-0.309*	-0.0915*	-0.135***
	(0.129)	(0.141)	(0.121)	(0.183)	(0.046)	(0.033)
	[0.787]	[0.482]	[0.798]	[0.069]	[0.051]	[0.001]
Pill Mill Bill	-0.213	-0.0598	-0.258*	-0.0497	-0.205**	-0.000909
	(0.127)	(0.125)	(0.146)	(0.136)	(0.085)	(0.029)
	[0.121]	[0.372]	[0.085]	[0.417]	[0.028]	[0.493]
Observations	2714	2713	2692	2714	3070	3066
Fixed Effects	X	X	X	X	X	X
Controls	X	X	X	X	X	X
Linear Trends						
Medicaid Weights	X	X	X	X		
Population Weights					X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data is by state and quarter. Standard errors in parentheses, clustered by state.
Wild cluster bootstrapped p-values in brackets.
The PDMP, Mandate, and Pill Mill rows contain coefficient estimates for variables indicating the timing of Prescription Drug Monitoring Programs, a Mandate that requires practitioners to check the PDMP, or a "Pill Mill" Bill that imposes many strict regulations on clinics that prescribe and dispense opioids on site.
Columns (1), (2), (3), and (4) show the effect of the PDMP on oxycodone, weak dose oxycodone, strong dose oxycodone, and hydrocodone per Medicaid enrollee in the Medicaid data. Columns (5) and (6) display the effect of the PDMP on ARCOS aggregate oxycodone and hydrocodone shipments per capita.
Weak dose oxycodone has 10 or fewer milligrams per pill; strong dose oxycodone has greater than 10 milligrams per pill.

Table 6: The Effect of Policies on Heroin Incidents Per Capita, Across Model Specifications

	FE	Controls	LTT	Factor
Panel A: All 735 Counties				
PDMP	0.150	0.346	0.457	0.0618*
	(0.356)	(0.359)	(0.437)	(0.0184)
		[0.792]		[0.058]
Observations	92292	92292	92292	92292
Panel B: Bottom 90% of Oxycodone Density Counties				
PDMP	-0.127	0.00710	-0.0291	0.0576**
	(0.193)	(0.155)	(0.120)	(0.0178)
		[0.486]		[0.036]
Observations	82704	82704	82704	82704
Panel C: Top 10% of Oxycodone Density Counties				
PDMP	1.787	2.093*	2.203**	1.166***
	(1.264)	(0.934)	(0.897)	(0.159)
		[0.940]		[0.001]
Observations	9588	9588	9588	9588
Fixed Effects	X	X	X	
Controls		X	X	
Linear Time Trends			X	$\hbar$
Population Weights	X	X	X	X
Factor Model				X
Cluster Bootstrap		X		X

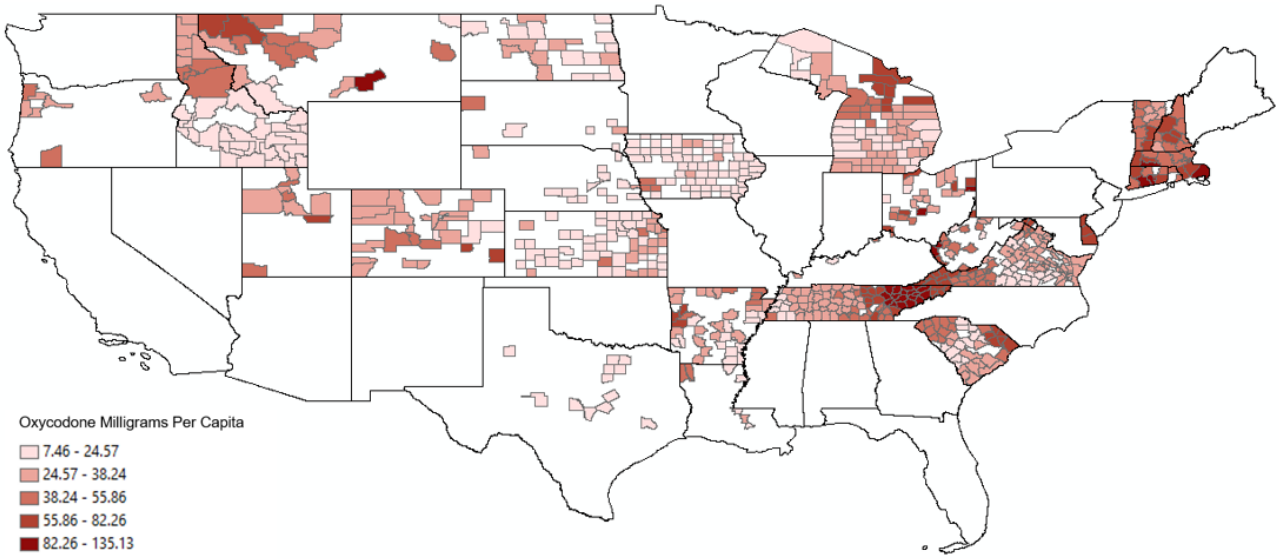
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parentheses and are clustered on the treament level (state). Wild cluster boostrap p-values are listed in brackets.
Panel A shows coefficients on policies when models are run on all 735 counties. Panel B and Panel C show heterogeneity of policy effects across counties depending on pre-policy oxycodone milligrams per capita. Panel B shows the coefficients of the models run on a subsample of the data containing only the bottom 90% of oxycodone-dense counties, and Panel C shows results from models run on the top 10% most oxycodone-dense counties.
Data source: NIBRS 2004-2014.
$\hbar$: The IFE Factor Model nests fixed effects and county-specific linear time trends.

Table 7: The Effect of the PDMP on Drug Crimes Per Capita

Incidents Per 100,000 Pop Per Month	Heroin		Opiates	
	Incidents	Possible Dealers	Incidents	Possible Dealers
Panel A: All 735 Counties				
PDMP	0.346	0.013	-0.162	-0.0174
	(0.359)	(0.0672)	(0.0956)	(0.0257)
	[0.792]	[0.430]	[0.243]	[0.246]
Mean Level	1.30	0.50	2.18	0.52
Observations	24780	24384	24384	24384
Panel B: Low Oxycodone Density Counties				
PDMP	0.007	-0.0317	-0.651	0.014
	(0.155)	(0.0483)	(0.0774)	(0.0248)
	[0.486]	[0.237]	[0.441]	[0.514]
Mean Level	1.12	0.43	1.87	0.43
Observations	21096	20964	20964	20964
Panel C: High Oxycodone Density Counties				
PDMP	2.093*	0.324*	-0.547	-0.248
	(0.934)	(0.140)	(0.213)	(0.0971)
	[0.940]	[0.918]	[0.131]	[0.150]
Mean Level	2.34	0.95	4.01	1.66
Observations	3684	3420	3420	3420
Fixed Effects	X	X	X	X
Controls	X	X	X	X
Linear Time Trends				

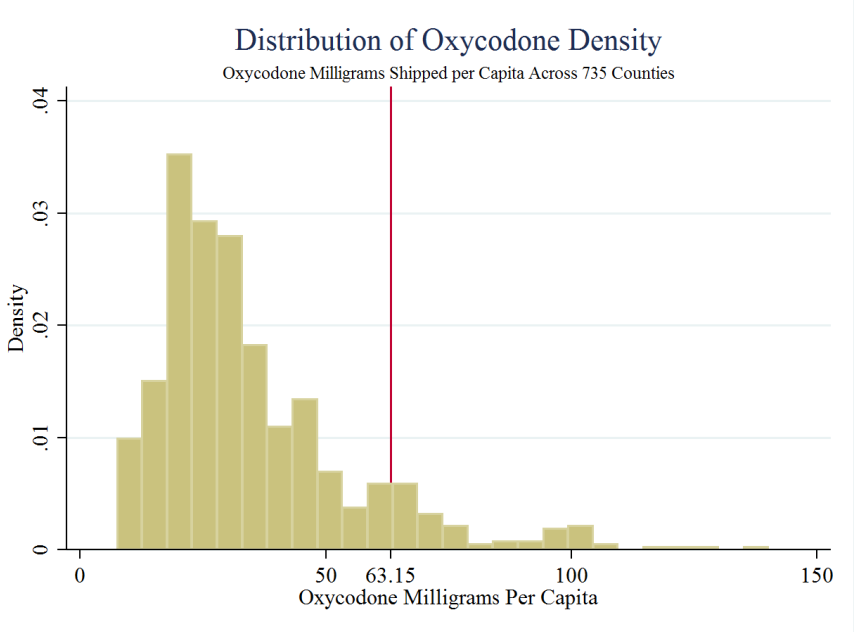
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parentheses, clustered by state. Wild cluster p-values in brackets. Difference-in-differences regression model specification includes county and month fixed effects, county controls, and population weights.
In Panel B and Panel C, the data are subdivided into the bottom 90% of least oxycodone dense counties and the top 10% of most oxycodone dense counties. Crime data: NIBRS 2004-2014. Oxycodone density data: DEA ARCOS.

Figure 1: NIBRS County Oxycodone Density



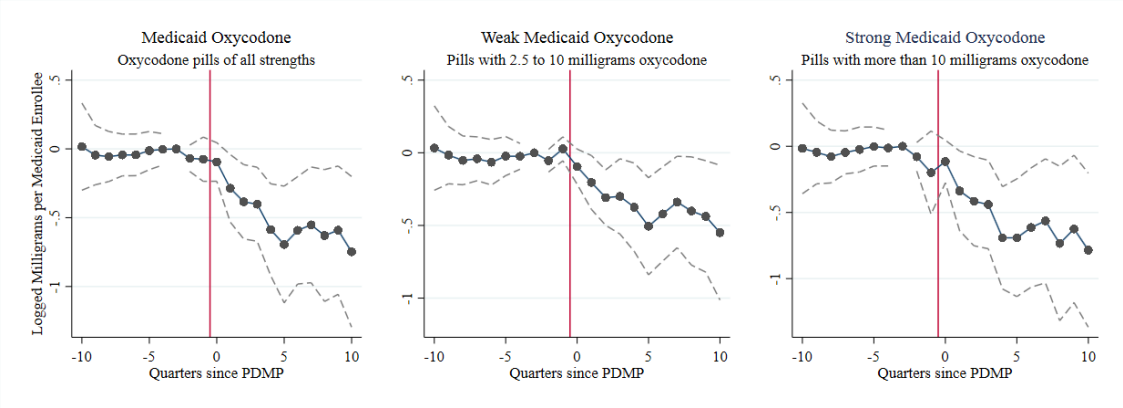
The figure displays the NIBRS-covered counties colored by oxycodone milligrams per person. Darker counties are more oxycodone dense. Oxycodone density data: DEA ARCOS.

Figure 2: The Distribution of Oxycodone Per Capita Across Counties



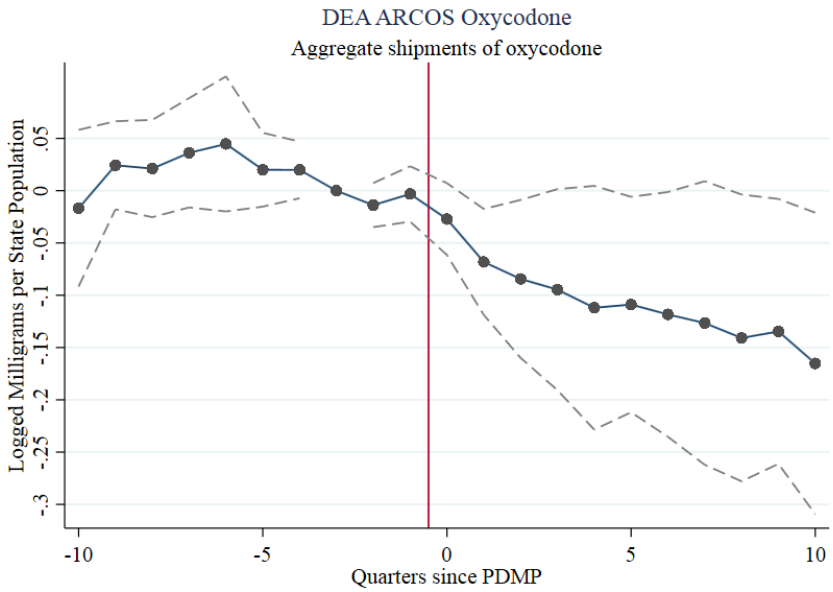
Notes: The figure plots the distribution of 2004 oxycodone density across 735 counties. The top 10% most oxycodone dense counties have greater than 63.15 milligrams of oxycodone per capita per month, equivalent to 6-12 weak dose pills or 2-3 strong dose pills per month for each resident. The PDMP has larger effects on counties that have higher pre-policy (year 2004) oxycodone density. Heroin incident data: NIBRS. Oxycodone density data: DEA ARCOS.

Figure 3: PDMP on Medicaid Oxycodone Outcomes Over Time



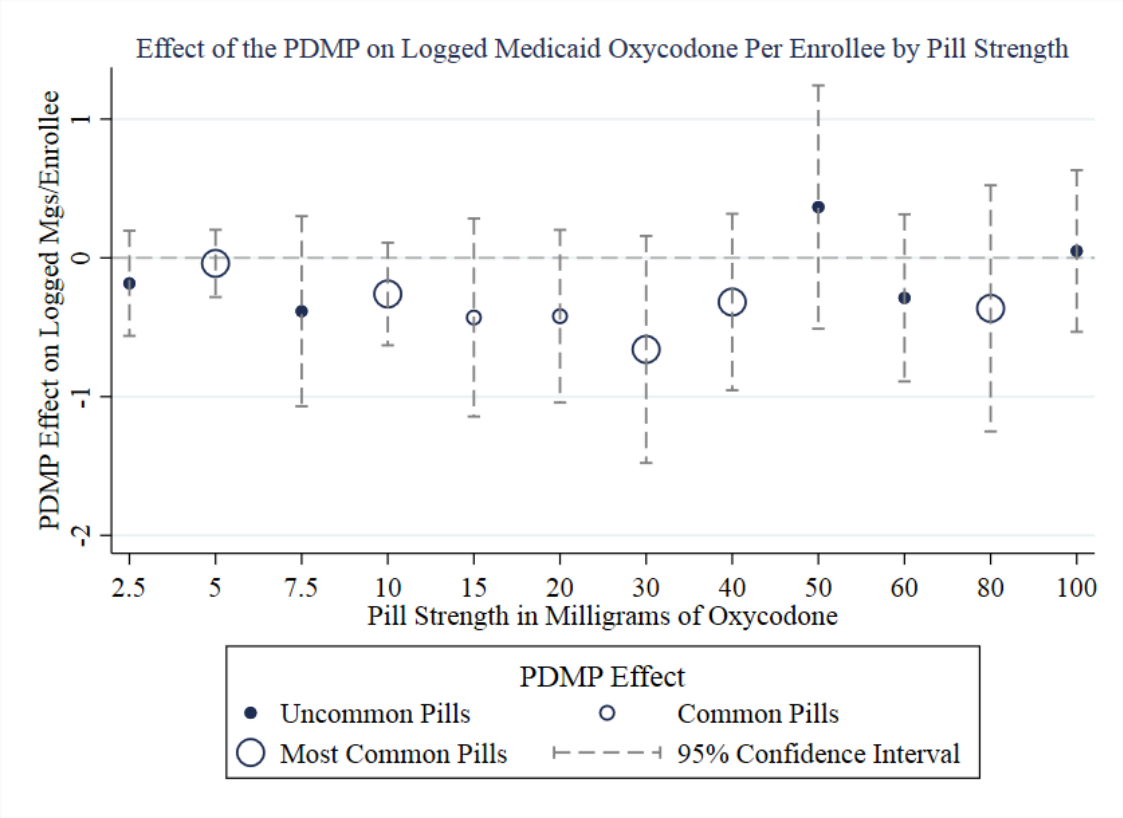
Notes: The figures plot coefficients on lag and lead policy indicators from difference-in-differences models on logged amounts of oxycodone by Medicaid prescriptions (milligrams per capita). The dependent variable is restricted to weak dose oxycodone in the center graph and strong dose oxycodone in the right graph. The graphs correspond to event-study adaptations of Columns (1), (2) and (3) of Table 5 and models include state and time fixed effects, controls, population weights, and state-specific linear time trends. Data spans 50 states plus the District of Columbia quarterly from 2000-2015. Prescription Data: Medicaid SDUD

Figure 4: PDMP on Aggregate Oxycodone Shipments



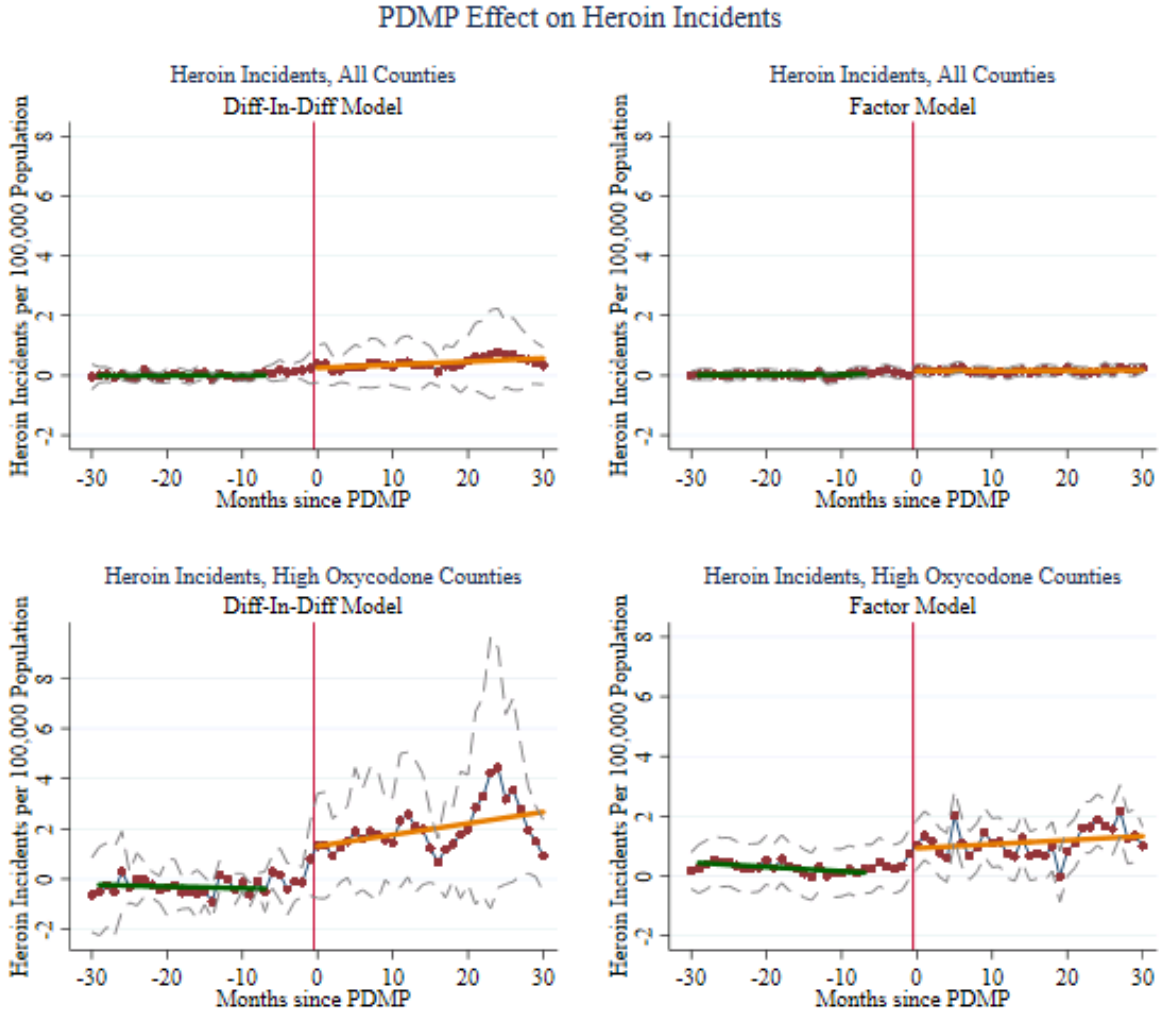
Notes: Same as Figure 4, except using aggregate shipments of oxycodone from ARCOS. The trends graphs correspond to Column (5) of Table 5 and includes state and time fixed effects, controls, population weights, and state-specific linear time trends. The dataset spans 50 states plus the District of Columbia quarterly from 2000-2015. Aggregate Shipment Data: DEA ARCOS

Figure 5: The Effect of the PDMP on Medicaid Oxycodone by Strength



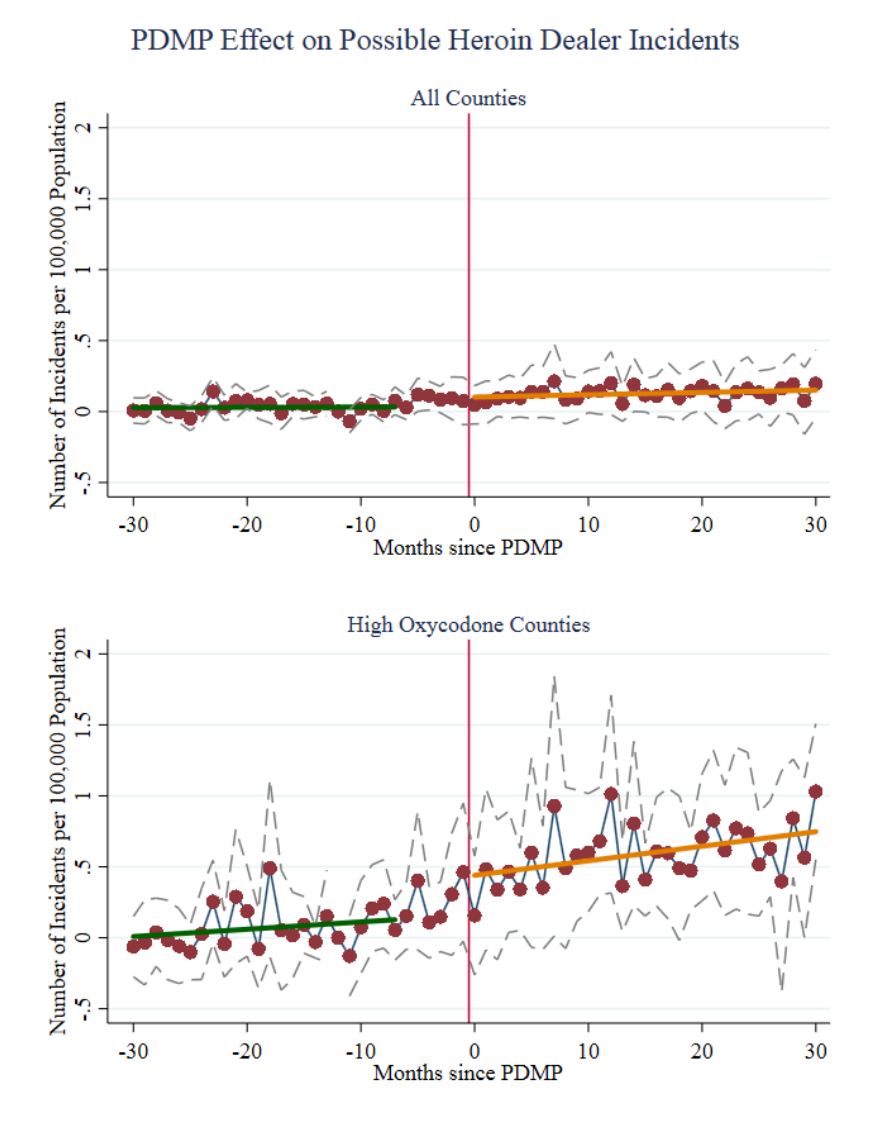
Notes: The figure plots the effect of the PDMP on logged Medicaid oxycodone per enrollee disaggregated by pill strength. Each plotted point is associated with a separate regression on milligrams per enrollee restricted to pills of each strength. Points are sized by the relative frequency of pills in the Medicaid data. "Uncommon Pills" are pills that make up less than 5% of oxycodone, "Common Pills" make up between 5% and 10% of oxycodone, and "Most Common Pills" are pills that make up for greater than 10% of oxycodone.

Figure 6: PDMP on Heroin Incidents Over Time



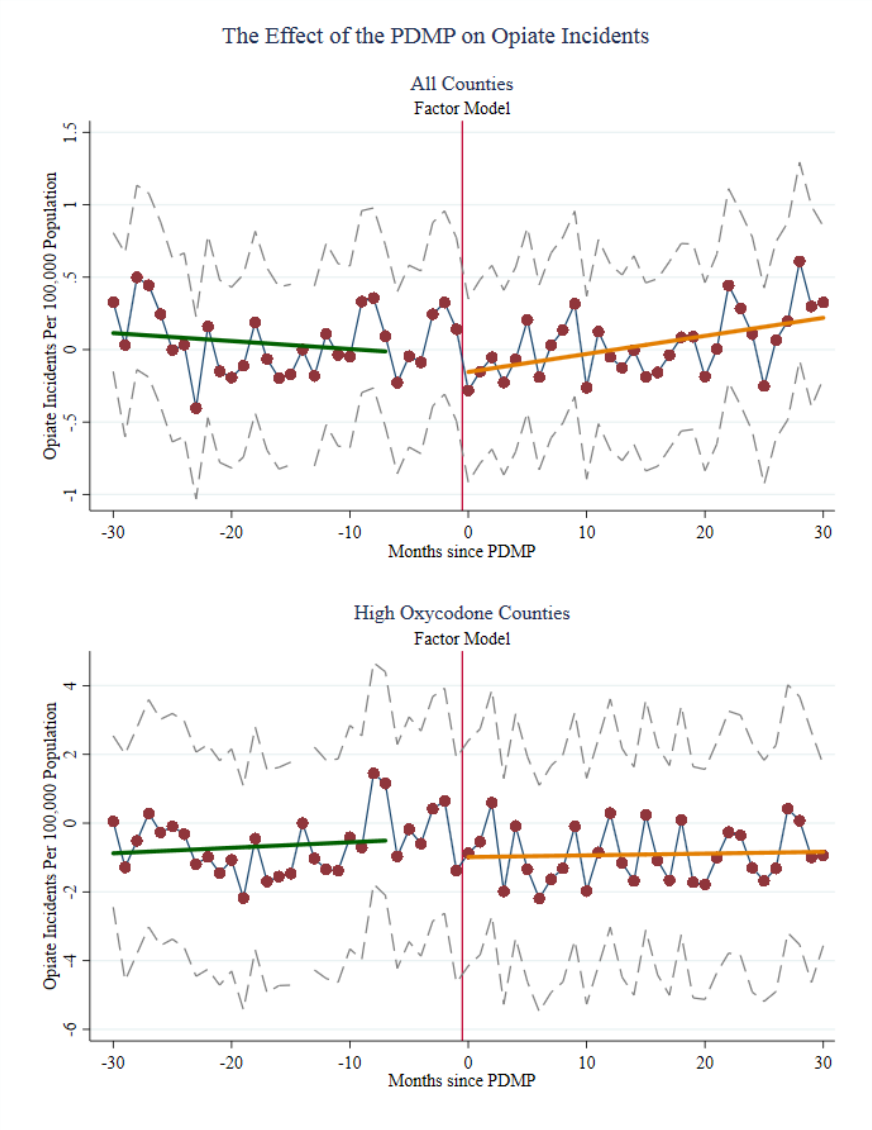
Notes: Graphs plot the coefficients on PDMP lags and leads indicators in difference-in-differences models (left graphs) and factor models (right graphs) on heroin incidents per 100,000 in a county-month pair. The top graphs show the PDMP effects on heroin incidents across all counties. The lower graphs show the PDMP effects on heroin incidents in the most oxycodone-dense counties. Event study regressions include month and county fixed effects, controls, and county-specific linear time trends and population analytic weights. The county data spans 735 counties over 26 states monthly from 2004-2014. Heroin incident data: NIBRS. Oxycodone density data: DEA ARCOS.

Figure 7: The Effect of the PDMP on Possible Heroin Dealers



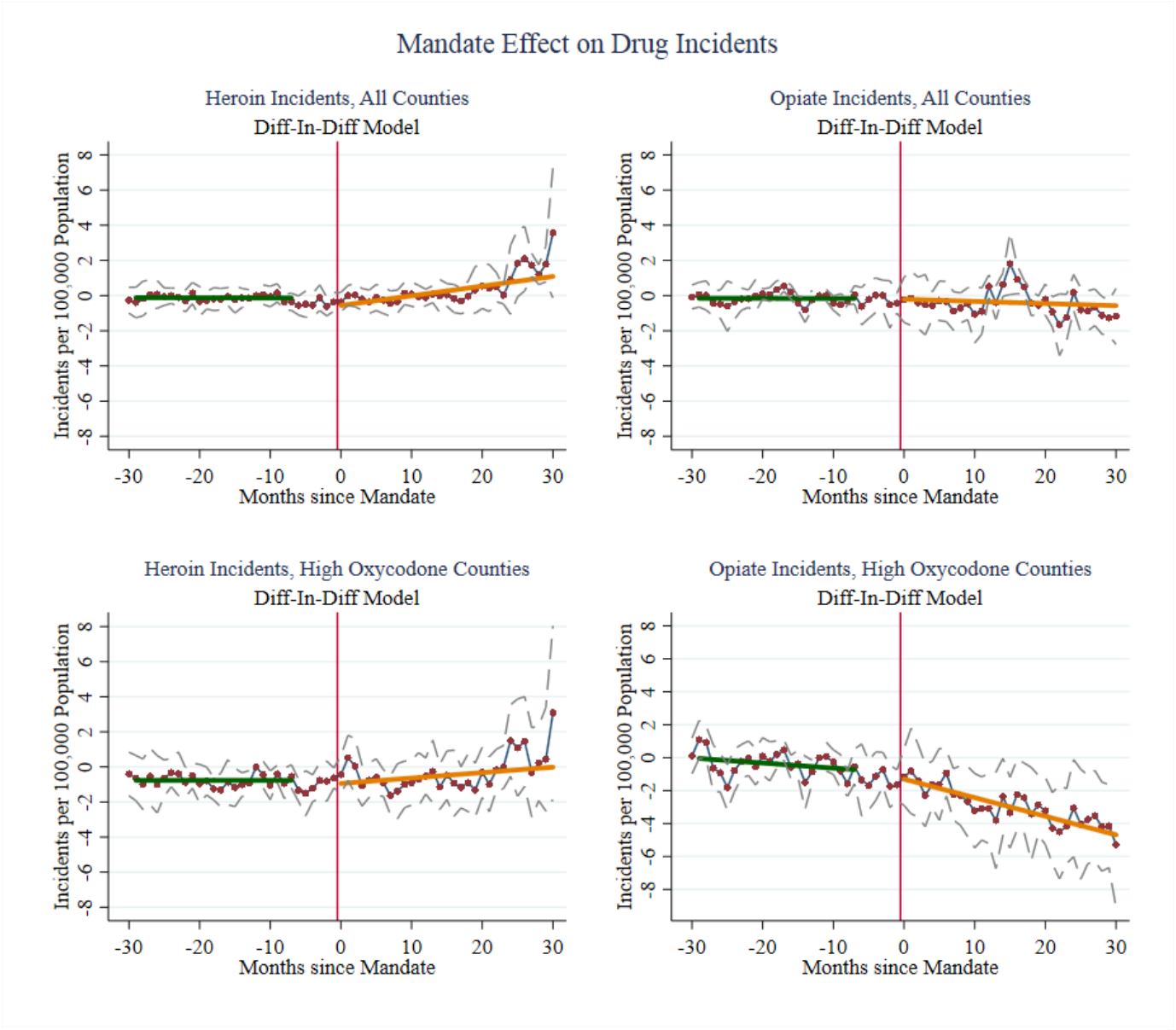
The event study graphs plot the effect of the PDMP on the rate over time of incidents involving possible heroin dealers in all counties and in counties with high oxycodone density. A possible heroin dealer incident is one where individuals 1.) are carrying more than 2 grams of heroin, 2.) Are carrying between 1 and 2 grams of heroin and a large amount of another drug, or 3.) Are carrying any heroin and were entered in the data as selling any drug. Weighted regressions include county and time fixed effects, controls, and county-specific linear time trends. Data source: NIBRS.

Figure 8: The Effect of the PDMP on Opiate Incidents



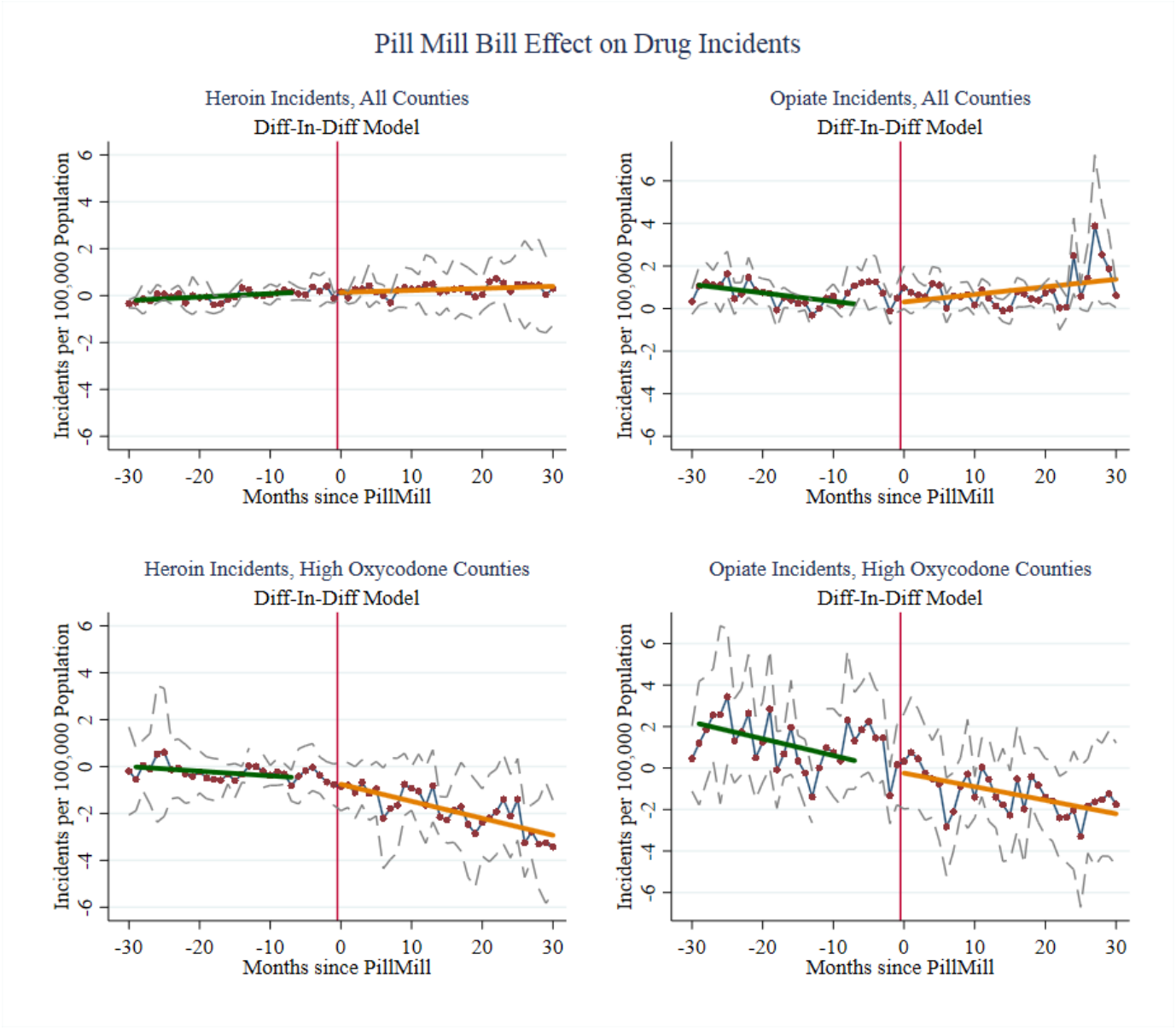
The graphs display the event study of the PDMP on Opiate Incidents per 100,000 population. The factor model is used because difference-in-differences specifications do not pass the parallel trends test, due to non-linear county-specific time trends that are captured using the factor model.

Figure 9: The Effect of the Mandate on Drug Incidents



The graphs display the event study of the Mandate on heroin incidents and opiate incidents per 100,000 population, over all counties and within the most oxycodone-dense counties.

Figure 10: The Effect of the Pill Mill Bill on Drug Incidents



The graphs display the event study of the Pill Mill crackdown on heroin incidents and opiate incidents per 100,000 population, over all counties and within the most oxycodone-dense counties.

Appendix A Summary Statistics Control Variables

Table A1: Summary Statistics of Controls for State Level Models

	N	Mean	Std. Error
Data: Census Bridged Population Estimates			
Fraction Aged 10-19	3,204	0.1396	0.0090
Fraction Aged 20-29	3,204	0.1383	0.0093
Fraction Aged 30-39	3,204	0.1362	0.0112
Fraction Aged 40-49	3,204	0.1445	0.0101
Fraction Aged 50-59	3,204	0.1297	0.0115
Fraction Aged 60-69	3,204	0.0885	0.0150
Fraction Aged 70+	3,204	0.0916	0.0246
Fraction Female	3,204	0.509	0.0056
Fraction Black	3,204	0.1326	0.0866
Fraction Hispanic	3,204	0.1484	0.1271
Fraction Other Non-White	3,204	0.0627	0.0441
Data: BLS Quarterly Census of Employment and Wages			
Fraction Employed Manufacturing	3,204	0.1236	0.0441
Fraction Employed Agriculture	3,204	0.0116	0.0108
Data: BLS Local Area Unemployment Statistics			
Unemployment Rate	3,204	0.0817	0.0405
Data: Census Historical Poverty Tables			
Poverty Rate	3,204	0.1363	0.0293
Data: Bureau of Economic Analysis			
Income Per Capita	3,204	$38,867	$7,867
Data: Medicaid Drug Utilization Data			
OxyContin mgs per Enrollee (2004)	3,204	31.39	17.46
Medicaid Pills Per Enrollee	3,204	23.297	13.64
Data: Centers for Medicare and Medicaid Services			
Fraction Medicare Enrolled	3,204	0.157	0.0221

Panel Data is by state and quarter. Income per capita is per year, and OxyContin milligrams per capita and Medicaid pill per enrollee are quarterly.

Table A2: Summary Statistics of Controls for County Level Models

	N	Mean	Std. Error
All 735 Counties			
Data: Census Bridged Population Estimates			
Fraction 10-19	92,292	0.1387	0.0139
Fraction 20-29	92,292	0.1348	0.0357
Fraction 30-39	92,292	0.1279	0.0167
Fraction 40-49	92,292	0.1437	0.0174
Fraction 50-59	92,292	0.1376	0.0160
Fraction 60-69	92,292	0.0955	0.0202
Fraction 70+	92,292	0.0925	0.0246
Fraction Female	92,292	0.5087	0.0127
Fraction Black	92,292	0.1181	0.1268
Fraction Hispanic	92,292	0.0687	0.0629
Fraction Other Non-White	92,292	0.0358	0.0370
Fraction 65+	92,292	0.1288	0.0389
Data: BLS Quarterly Census of Employment and Wages			
Fraction Employed Manufacturing	92,292	0.1479	0.0979
Average Week Wage	92,292	$790.70	$219.83
Pharmacies per 1,000 pop	92,292	1.64	0.738
Data: BLS Local Area Unemployment Statistics			
Unemployment	92,292	0.0551	0.0224
Data: Drug Enforcement Administration ARCOS Files			
Pre-2010 Oxycodone per capita	57,591	52.168	34.188
Data: FBI Uniform Crime Reporting LEOKA			
Officers per 1,000 pop	92,292	17.93	0.041

Panel Data is by county and month. 735 counties across 26 states have complete monthly coverage within the NIBRS dataset during the entire period of 2004 to 2014. Only counties with full coverage are used in the crime rate analysis.

Appendix B Discussion of PDMP Dates

Web-access dates for PDMPs vary, sometimes dramatically, across sources. Table B3 lists the NAMSDL provider access date, the PDAPS web access date, and an alternate set of dates that I obtained through various sources. The PDAPS and NAMSDL sometimes list the start date of on-paper or fax-based PDMPs, and launch dates for online systems are obtained from various other sources. The PDAPS and NAMSDL report consistent PDMP web access dates for 27 states. For 12 states, I found a physician access date that is different from both the NAMSDL and PDAPS, which provided dates for non-electronic PDMPs. I provide sources and explanations for each of these 12 differing dates in TableB4. For 8 states, either only the PDAPS or NAMSDL list the web access date. Missouri passed PDMP legislation in 2016 after the time period of interest for this paper. The remaining 2 states, Hawaii and Idaho, do not have consistent online documentation of their online physician-access dates.

Despite the differences in dates across data sources, my results are robust under many sets of dates and models. The PDAPS dates were chosen for the main tables in the paper. When the "Possible Dates" are used, the PDMP is not found to affect low-dose oxycodone pills; all the effect is through a reduction in high-dose pills.

Table B3: Comparison of PDMP Dates from Different Sources

State	NAMSDL Provider Access Date	PDAPS Web Access Date	Other Date	Comments
Alabama	August 2007	June 2007†	August 2007	NAMSDL used
Alaska	January 2012	January 2012	January 2012	Dates consistent
Arizona	December 2008	December 2008	December 2008	Dates consistent
Arkansas	March 2013	May 2013	March 2013	NAMSDL used
California	July 2009		July 2009	NAMSDL used
Colorado	February 2008	February 2008	February 2008	Dates consistent
Connecticut	July 2008		July 2008	NAMSDL used
Delaware	August 2012	August 2012	August 2012	Dates consistent
Florida	October 2011	October 2011	October 2011	Dates consistent
Georgia	July 2013	July 2013	July 2013	Dates consistent
Hawaii		January 1992§	June 1996	‡, Electronic start date unknown
Iowa	March 2009	March 2009	March 2009	Dates consistent
Idaho	July 2008	May 1999	July 2008	‡, Electronic start date unknown
Illinois			January 2008	‡, See references table
Indiana	July 2007		July 2007	NAMSDL used
Kansas	April 2011	April 2011	April 2011	Dates consistent
Kentucky	July 1999§	July 1999§	March 2005	‡, See references table
Louisiana	January 2009	January 2009	January 2009	Dates consistent
Maine	January 2005	January 2005	January 2005	Dates consistent
Maryland	January 2014	December 2013	January 2014	Dates consistent
Massachusettes			December 2010	‡, See references table
Michigan	February 2003	January 2003	February 2003	‡, See references table
Minnesota	April 2010	April 2010	April 2010	Dates consistent
Mississippi	December 2005	December 2005	January 2008	‡, See references table
Missouri				
Montana	October 2012	October 2012	October 2012	Dates consistent
Nebraska		April 2011	April 2011	PDAPS used
Nevada	April 1997§	July 1997§	October 2004	‡, See references table
New Hampshire	October 2014	October 2014	October 2014	Dates consistent
New Jersey	January 2012	January 2012	January 2012	Dates consistent
New Mexico	August 2005	August 2005	August 2005	Dates consistent
New York		January 2010	August 2013	‡, See references table
North Carolina	October 2007	October 2007	October 2007	Dates consistent
North Dakota		September 2007	September 2007	Dates consistent
Ohio	October 2006	October 2006	October 2006	Dates consistent
Oklahoma	July 2006		July 2006	NAMSDL used
Oregon	September 2011	September 2011	September 2011	Dates consistent
Pennsylvania			August 2016	‡, See references table
Rhode Island		January 2005§		‡, See references table
South Carolina	June 2008	September 2008†	June 2008	NAMSDL used
South Dakota	March 2012	March 2012	March 2012	Dates consistent
Tennessee		December 2006	December 2006	Dates consistent
Texas		January 1982§	August 2012	‡, See references table
Utah	January 1997§	January 1996§	January 2006	‡, See references table
Vermont	April 2009	April 2009	April 2009	Dates consistent
Virginia	June 2006	June 2006	June 2006	Dates consistent
Washington	January 2012	January 2012	January 2012	Dates consistent
West Virginia			March 2013	‡, See references table
Wisconsin	May 2013	May 2013 2013	May 2013	Dates consistent
Wyoming	July 2004	October 2004	July 2004	Dates consistent

†: the PDAPS has recorded the date that data collection started as the "start date" of the policy whereas I use the NAMSDL date for physician access to the PDMP as the active policy date.
§: the PDAPS/NAMSDL recorded the launch date of a non-electronic PDMP
‡: the main results are not driven by these states and are robust to dropping them.

Table B4: Paper Dates that Differ from Non-electronic PDAPS and NAMSDL Dates

State	My Date	Reason
Illinois	January 2008	A presentation by Illinois' Prescription Monitoring Program's IT specialist states that the program went online in 2008.
Kentucky	March 2005	Kentucky's PDMP launched in March 2005 according to a presentation by the PDMP program manager.
Massachusettes	December 2010	Documents from the Massachusettes government state that the online PDMP launched in 2010.
Michigan	February 2003	The Detroit News states that although Michigan established its PDMP, "MAPS" was nearly unusable until it's update in April 2017.
Mississippi	January 2008	Mississippi Board of Pharmacy and PDMP Assist state that web access began in 2008, but data collection began April 2005.
Nevada	October 2004	According to an article in Business Wire, the Nevada PDMP was operational October 2004.
New York	August 2013	It is not clear when New York launched its original electronic PDMP, but was updated and improved in August 2013. Source: NY CMS
North Dakota	September 2007	Data from January 2007-August 2007 was retrospectively recorded into the online PDMP when it launched in September 2007. Source: PDMP Assist
Pennsylvania	August 2016	An article from the Governor's office states that the PDMP was launched in August 2016.
Rhode Island	September 2012	The system came online in September 2012, according to the Providence Journal and the Rhode Island Center for Medicare and Medicaid Services.
Texas	August 2012	Physicians gained access to the online PDMP in August 2012, according to the Texas Medical Liability Trust and the Texas Academy of Family Physicians
Utah	January 2006	Several dates are listed online, as early as 2002.
West Virginia	March 2013	I use the date of the automated flagging system which launched in 2013. The PDMP launched sometime in 2004. Source: WV CMS. WV doesn't drive results

Table B5: The Effect of the PDMP on Oxycodone and Heroin Incidents Under Different Dates

	Oxycodone Prescriptions				ARCOS Oxycodone		Heroin Incidents	
	All Medicaid		High Dose				High Oxy Counties	
	PDAPS	My Dates	PDAPS	My Dates	PDAPS	My Dates	PDAPS	My Dates
PDMP	-0.368**	-.316**	-0.382**	-0.307**	-0.067**	-0.0601	2.093*	1.534
	(0.157)	(0.130)	(0.128)	(0.035)	(0.058)	(0.130)	(0.934)	(1.387)
	[0.022]	[0.012]	[0.049]	[0.039]	[0.046]	[0.230]	[0.943]	[0.915]
Observations	2714	2714	2714	2714	2714	2714	9588	9588

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parentheses, clustered by state.
Wild cluster p-values in brackets.

Appendix C The Interactive Fixed Effects Model

Appendix C.1 The Interactive Fixed Effects Factor Model

The interactive fixed effects (IFE) factor model as detailed in Bai (2009) accounts for (possibly non-linear) geography-specific time trends while nesting fixed effects of time and county (state), accomplished by adding a principal component analysis structure to the error term. The IFE factor model assumes that patterns in opioid and heroin abuse within counties (states) can be modeled as a function of R unobserved linear factors, F_{rt}. The optimal number of factors, R, are chosen using criteria in Bai and Ng (2002).

$$AbuseOutcome_{ct} = \alpha + \beta PDMP_{ct} + \eta Mandate_{ct} + \phi PillMillBill_{ct} + \Psi X_{ct} + \Sigma_{r=1}^{R} \lambda_{rc} F_{rt} + u$$

The above equation outlines the IFE factor model structure, where F_{rt} is an unobserved factor, common across all counties (states) in month (quarter) t, and λ_{rc} is a county (state) factor loading, constant over time.

The factors, F_{rt}, can be thought of as nationwide time trends in opioid or heroin abuse to which different counties (states) are either more or less susceptible, depending on unobservable characteristics of those counties (states). The basic difference-in-difference model

accounts for national non-linear patterns in abuse, and the IFE factor model extends this by accounting for additional non-linear time trends that affect areas to varying degrees. For example, when I apply the factor model to heroin crime-rates, the factor model produces factors that plot out a gradual increase in heroin crime from 2004-2010, which then increases exponentially from 2010-2014. Counties experience the non-linear increase in heroin to differing degrees, which is accounted for in each county's factor loading. In the case of heroin crime incidents, a county's factor loading is correlated with its 2004 level oxycodone milligrams per capita, implying that more opioid-dense counties are more sensitive to the increase in heroin crime. This is consistent with the original hypothesis that restricting opioids causes more heroin use.

For factor model analysis on heroin incidents, the IFE factor model could in theory be approximated by adding linear, quadratic, and cubic geography-specific time trends to a difference-in-differences regression, but that comes at the cost of efficiency and statistical power. In practice, however, rather than adding a linear, quadratic, and cubic time trend for each of 735 counties, the factor model uses a matrix structure based on principle components analysis to account for several flexible time trends and assign factor loadings for each time trend by county. This factor approach uses fewer degrees of freedom while controlling for flexible time trends and therefore results in more precisely measured-estimates. The IFE factor model serves as a robustness check to my difference-in-differences model, and the point estimates are typically similar across both model specifications. Factor model results are covered in detail in the results section.

Appendix C.2 Results from the Interactive Fixed Effects Factor Model

Results calculated from the difference-in-differences models and IFE factor model are similar in regressions on prescription outcomes, likely because trends at the state-level are mitigated with aggregation. In contrast, difference-in-differences results and factor model results diverge more in the heroin models because of non-linear time trends at the more disaggregated county-level. When applied to the model on heroin incidents, the factor model produces

time trends that appear to fit non-linear county-specific time trends that the difference-in-differences model with county-specific *linear* time trends is not able to capture.

The factor model nests nationwide time trends accounted for in typical difference-in-differences models, and Figure C1 graphs a polynomial fit of the nationwide trend in race of heroin incidents by county. The nationwide time trends in Figure C1 does not account for differences in time trends across counties.

Figure C2 shows the "Factor 1" time trend from the IFE factor model. Factor 1 is a nationwide time trend experienced differently by individual counties depending on county factor loadings. August 2010 is the month when Purdue Pharmaceutical released the abuse-deterrent reformulation of OxyContin. Notice that Factor 1 shows a non-linear pattern of heroin incidents over time. Between January 2004 and August 2010, the rate of heroin incidents increases modestly, and then dramatically after August 2010. In the county-level regressions, I control for county-specific level responses to the tamper-proof reformulation by multiplying a post-August-2010 dummy indicator by each county's pre-reformulation oxycodone density.[30] Controlling for a level shift allows the abuse-deterrent reformulation to affect counties proportional to their likely abuse exposure, which does not fit the curvature of heroin incidents after 2010 well, as the factor model's first factor and nationwide time fixed effects trends pick up a dramatic increase in heroin incidents beginning in August 2010.[31] Figure C3 contains a map of the NIBRS counties' Factor 1 loadings. The darkest-color counties in Delaware, Oregon, Ohio, West Virginia, and Virginia experience the steepest increases in heroin incidents after 2010.

Counties' Factor 1 loadings are correlated with their 2004 density of ARCOS oxycodone, meaning more opioid-dense counties experience greater heroin transition after 2010. As an illustrative example, I have chosen two example counties, and graphed their heroin incident rates over time. Figure C4 displays the rate of heroin incidents in Spotsylvania County, VA, which the IFE model had assigned a large factor loading (90th percentile) and Florence County, SC which the IFE model had assigned a typical factor loading (50th percentile). The rate in Spotsylvania County shows more of a non-linear incident pattern, realizing a

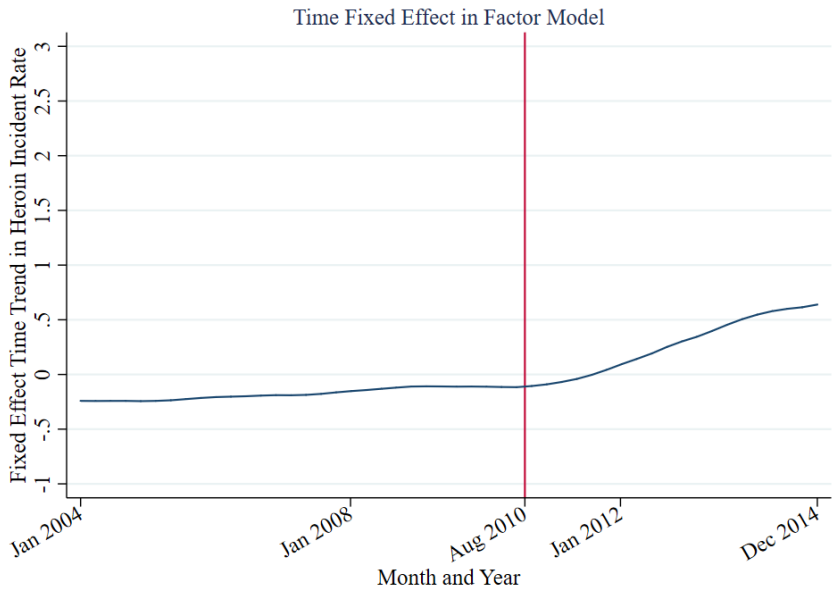
[30] Alpert et al. (2017) and Evans et al. (2018) use a similar method.

[31] Factor 1 is by construction orthogonal to the variable that proxies the OxyContin reformulation, and is perhaps picking up additional unexplained variation across counties not captured by the proxy.

dramatic increase in the 2010s. Figure C5 shows the heroin incident rate over time of the same counties, after removal of the controls and the county and time fixed effects. The figure approximates what the difference-in-differences model is left to fit with county-specific linear time trends after other covariates and fixed effects are controlled for, providing a poor fit to counties like Spotsylvania. Using county-specific linear time trends, the increase in heroin incidents after 2010 will likely fall above the fitted trend, and may be falsely attributed to the PDMP.

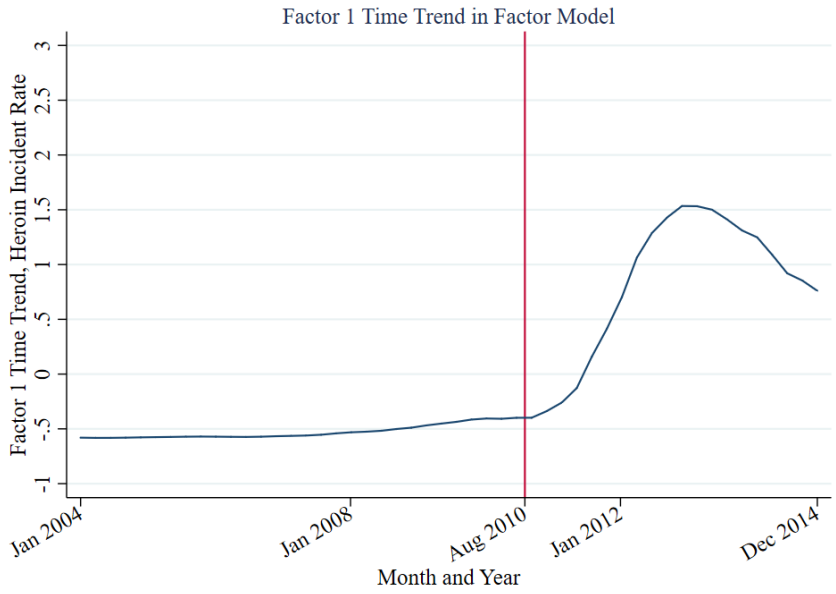
Table C6 compares the results of various difference-in-difference models with those of the IFE factor model. The coefficients resulting from the difference-in-differences models under linear time trends is 0.384, larger than the model without time trends (0.239). Adding quadratic and cubic county-specific time trends for the regressions on all counties results in a PDMP coefficient estimate of 0.108 additional heroin incidents per 100,000 population per month, which is closer to the IFE factor model estimates (0.112) because the county-specific polynomials capture the curvature in heroin incidents within counties. The IFE model consistently provides an estimate around 1 additional heroin incident per 100,000 population per month in the oxycodone-dense counties, about a 40% increase.

Figure C1: The Nationwide Time Trend in Heroin Incidents, Obtained from the IFE Factor Model



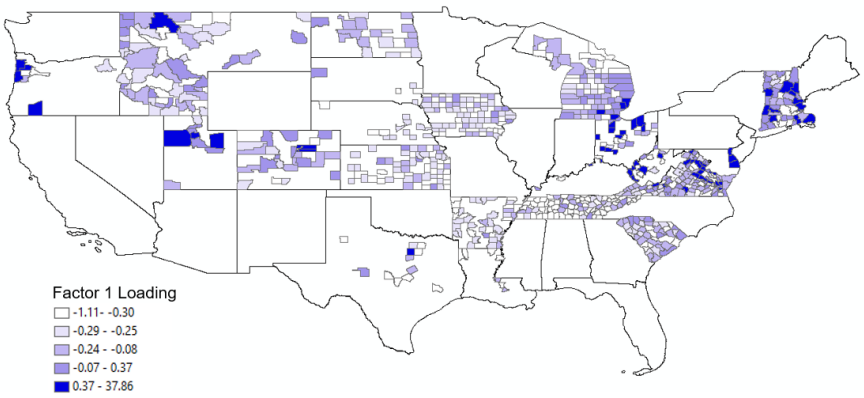
Notes: The figure shows the average time trend (time fixed effects) in the heroin incident rate from the IFE factor model. Heroin incident data: NIBRS.

Figure C2: Factor 1 From the Interactive Fixed Effect Factor Model on Heroin Incident Rate



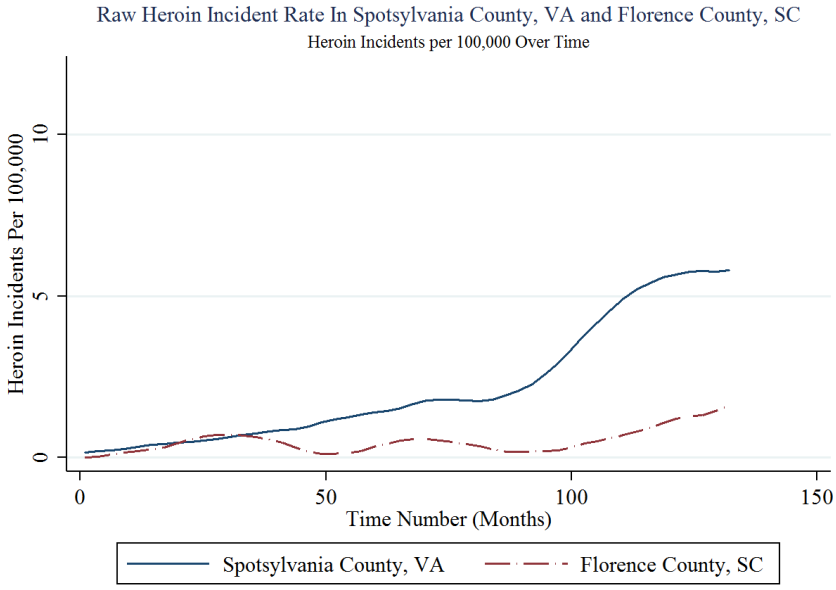
Notes: The graph plots the IFE factor model's factor 1 time trend. The red line marks the OxyContin reformulation that made it harder to abuse. Within the IFE factor model, Factor 1 is the time trend that accounts for the most residual variance.

Figure C3: Counties by Factor 1 Loadings



Notes: The map displays counties from the NIBRS data colored by each county's sensitivity to the Factor 1 time path from the interactive fixed effects factor model as shown in Figure C2. Factor 1 may be picking up differences in county responses to the OxyContin reformulation, and the dark-colored counties perhaps have exceptional sensitivity to the reformulation.

Figure C4: Heroin Incident Rate in Two Example Counties



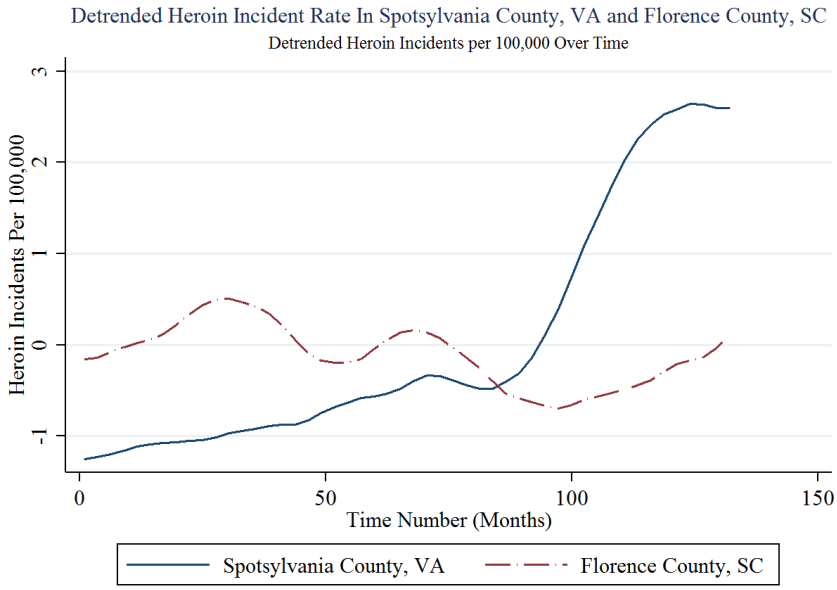
Notes: The graph compares the raw heroin incident rate over time in 2 counties with approximately 100,000 population. Spotsylvania County, VA is assigned a high factor 1 loading and Florence County, SC is assigned an average factor 1 loading under the IFE factor model. The factor 1 time trend captures a non-linear increase in the heroin incident rate over time, as seen in Figure C2, and Spotsylvania County's data corresponds with factor 1's more dramatic exponential growth in the heroin incident rate over time.

Table C6: Effect of PDMP on Heroin Incidents: Comparison of Models

	Difference-In-Differences			IFE Factor Model	
	Controls	LTT	PTT	Factor	Wt. Factor
Panel A: All Counties					
PDMP	0.0792	0.108	0.111	0.112*	0.120**
	(0.161)	(0.203)	(0.277)	(0.059)	(0.055)
Mandate	1.181	0.873	0.128	0.129	0.406
	(0.862)	(0.589)	(0.245)	(0.308)	(0.412)
Pill Mill Bill	-0.511	0.297	0.105	0.089	0.111
	(0.762)	(0.678)	(0.176)	(0.612)	(0.461)
Observations	92292	92292	92292	92292	92292
Panel B: Top 10% Oxycodone Density Counties					
PDMP	0.915	1.414*	1.534*	1.007***	0.714*
	(0.713)	(0.756)	(0.717)	(0.303)	(0.399)
Mandate	2.168**	1.571***	-0.395	1.990***	1.803**
	(0.979)	(0.303)	(0.506)	(0.664)	(.757)
Pill Mill Bill	-3.083**	-2.627**	-0.911*	-1.154***	-1.251***
	(1.200)	(0.875)	(0.474)	(0.547)	(0.688)
Observations	9588	9588	9588	9588	9588
Fixed Effects	X	X	X	$\hbar$	$\hbar$
Controls	X	X	X	X	X
Popln. Weight	X	X	X		X
Linear Time Trends		X	X	$\hbar$	$\hbar$
Quadratic Time Trends			X	$\hbar$	$\hbar$
Cubic Time Trends			X	$\hbar$	$\hbar$

$\hbar$: The IFE Factor Model nests fixed effects and county-specific polynomial time trends. The "controls" specification includes county demographic and economic controls, as well as county and time fixed effects. The "LTT" specification adds county-specific linear time trends, and "PTT" adds county-specific polynomial time trends by controlling for a quadratic and cubic time trend within counties.

Figure C5: The Detrended Heroin Incident Rate in Two Example Counties



Note: The figure shows the heroin incident rate with the national time trends, county fixed effects, and controls removed, for Spotsylvania County, VA and Florence County, SC, which both have approximately 100,000 residents. The figure suggests that the difference-in-difference specification alone does not capture the non-linear increase in the heroin incident rate in Spotsylvania County and counties like it. Spotsylvania and similar counties are assigned a high factor 1 loading under the IFE factor model, and factor 1 controls for a non-linear county-specific growth rate in heroin incidents. In contrast, Florence County, SC follows the national time trend more closely and is not assigned a high factor 1 loading.

Appendix D Additional Robustness Checks

Appendix D.1 Placebo Test and Wild Cluster Bootstrap

Due to concerns about autocorrelation and few treated states in the panel data, wild cluster bootstrapped p-values are used to draw inference for all main results. Coefficients on the PDMP remain significant for regressions on Medicaid oxycodone, Medicaid strong oxycodone, ARCOS oxycodone, and heroin incidents among oxycodone-dense counties.

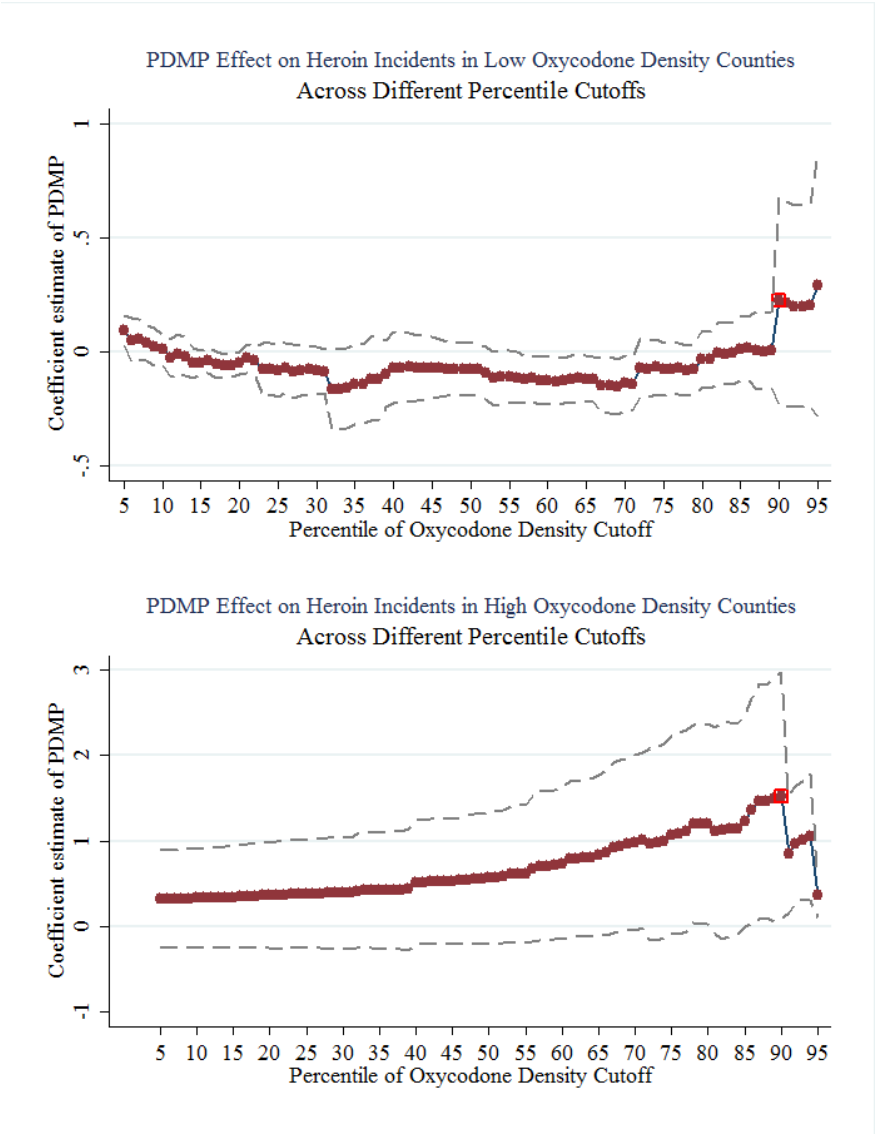
Concerns about autocorrelation are especially pertinent to difference-in-differences regressions on addictive opioid drugs, which have a highly correlated temporal pattern. Under a placebo test as suggested in Bertrand et al. (2004), models of the PDMP, Mandate and Pill Mill are found to over-reject the null. The problem is most acute for the Mandate policy and the Pill Mill Bill regulation, with 5% placebo rejection rates around 20% and 35%, respectively, likely because of few treated states for either policy. Rejection rates of the placebo PDMP policy range from 6% to 30%, with the main prescription results on oxycodone only slightly over-rejecting at the 6-8% level. This may mean that in this study, difference-in-differences estimates are overly lax in rejection.

To remedy the over-rejection problem, I use the Wild Cluster Bootstrap t-statistic-percentile procedure outlined in Cameron, Gelbach, Miller (2008). P-values obtained from the proposed t-statistic procedure and are included in brackets for key results in Table 5, Table D7 and Table 7. IFE factor model results are cluster-bootstrapped as well.

Appendix D.2 Jurisdiction Selection into the NIBRS

Police jurisdictions opt into the NIBRS, so it is possible that results on drug-related crimes do not generalize across counties. However, counties containing jurisdictions that opt into the NIBRS have fewer opioid problems and results showing that policies cause an increase in heroin incidents will therefore may be biased downward due to possible selection. Table D8 compares summary statistics of all US counties, and counties split into the NIBRS sample and Non-NIBRS sample. NIBRS counties typically cover a smaller population, have larger relative white populations and smaller relative Hispanic populations. The counties are

Figure D6: Sensitivity of the Estimated Effects on Heroin Incident Rate Using Different Thresholds to Define High/Low Oxycodone Density Counties



The top figure plots the PDMP estimated coefficients in the less oxycodone dense counties, depending on the threshold (in oxycodone per capita distribution percentile) used to classify counties as "low oxycodone dense" counties. The bottom figure plots the PDMP coefficients for the more oxycodone dense counties, depending on the threshold (in oxycodone per capita distribution percentile) used to classify counties as "high oxycodone dense" counties. The main tables use the 90th percentile as the cutoff. Coefficients are obtained by running a difference-in-differences regression (including county and month fixed effects, controls and analytic weights) on heroin incidents on subsets of counties that are below or above the thresholds.

slightly more female-heavy, have a larger proportion of their workforce employed in manufacturing, and have a smaller portion of their workforce employed in agriculture. In terms of drug offenses, the NIBRS counties realize lower rates of drug possession offenses but higher

rates of alcohol-related minor offenses (drunkenness) than their counterparts not covered in the NIBRS. NIBRS counties are similar to non-NIBRS counties in the age breakdown of their population, wages, unemployment rate, and rate of drug sales.

Table D7: The Effect of Policies on Heroin Incidents Per Capita, Across Model Specifications

	OLS	FE	Controls	LTT	Factor
Panel A: All 735 Counties					
PDMP	0.466***	0.0792	0.108	0.300	0.112*
	(0.0382)	(0.161)	(0.203)	(0.277)	(0.059)
			[0.654]		[0.058]
Mandate	3.774***	1.181	0.873	0.128	0.123
	(0.226)	(0.862)	(0.589)	(0.245)	(0.308)
			[0.881]		[0.689]
Pill Mill Bill	-1.597***	-0.511	-0.297	0.105	0.111
	(0.181)	(0.762)	(0.678)	(0.176)	(0.312)
			[0.365]		[0.722]
Observations	92292	92292	92292	92292	92292
Panel B: Bottom 90% of Oxycodone Density Counties					
PDMP	0.672***	-0.0721	-0.0492	0.00204	0.095**
	(0.0359)	(0.0538)	(0.0755)	(0.0844)	(0.045)
			[0.236]		[0.036]
Mandate	1.689***	0.255	-0.0341	0.0702	-0.023
	(0.202)	(0.762)	(0.746)	(0.155)	(0.137)
			[0.449]		[0.869]
Pill Mill Bill	0.623***	0.525	0.752	0.303*	0.136
	(0.150)	(0.852)	(0.763)	(0.164)	(0.273)
			[0.794]		[0.618]
Observations	82704	82704	82704	82704	82704
Panel C: Top 10% of Oxycodone Density Counties					
PDMP	0.0462	0.915	1.414*	1.534*	0.972***
	(0.139)	(0.713)	(0.756)	(0.717)	(0.303)
			[0.915]		[0.001]
Mandate	5.545***	2.168**	1.571***	-0.395	2.003***
	(0.312)	(0.979)	(0.303)	(0.506)	(0.661)
			[0.999]		[0.002]
Pill Mill Bill	-6.104***	-3.083**	-2.627**	-0.911*	-1.174**
	(0.301)	(1.200)	(0.875)	(0.474)	(0.551)
			[0.026]		[0.033]
Observations	9588	9588	9588	9588	9588
Fixed Effects		X	X	X	
Controls			X	X	
Linear Time Trends				X	$\hbar$
Population Weights	X	X	X	X	X
Factor Model					X
Cluster Bootstrap			X		X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parentheses and are clustered on the treament level (state). Wild cluster boostrap p-values are listed in brackets.

Panel A shows coefficients on policies when models are run on all 735 counties. Panel B and Panel C show heterogeneity of policy effects across counties depending on pre-policy oxycodone milligrams per capita. Panel B shows the coefficients of the models run on a subsample of the data containing only the bottom 90% of oxycodone-dense counties, and Panel C shows results from models run on the top 10% most oxycodone-dense counties.

Data source: NIBRS 2004-2014.

$\hbar$: The IFE Factor Model nests fixed effects and county-specific linear time trends.

Table D8: Comparison of NIBRS and Non-NIBRS Counties

Area	U.S. Counties	Non-NIBRS	NIBRS Counties
Number of Counties	3,241	2,506	735
Population	1,096,302	1,270,311	550,712
Demographics			
% White	65.32	62.60	73.84*
% Black	12.75	12.59	13.27
% Hispanic	15.93	18.11	9.08*
% Other Race	5.99	6.69	3.80*
% Female	50.83	50.79	50.98*
% Age 10-19	13.88	13.85	13.97
% Age 20-29	13.87	13.87	13.87
% Age 30-39	13.22	13.28	13.07
% Age 40-49	14.29	14.29	14.31
% Age 50-59	13.36	13.30	13.53
% Age 60-69	9.17	9.18	9.15
% Age 70+	9.11	9.18	8.90
Economy			
% Workforce Manufacturing	12.28	11.81	13.73*
% Workforce Agriculture	1.36	1.53	0.81*
% Unemployed	5.58	5.55	5.68
Weekly Wage	$827.36	827.84	$825.88
Opioid Exposure			
Pharmacies Per 100,000	165.4	167.8	158.1
Oxycodone Mgs Per Capita	60.23	59.57	62.31
Drug Crimes from UCR			
Drug Offenses	496.97	515.47	438.99*
Synthetic Sales	7.68	8.55	4.96
Synthetic Possession	18.46	19.12	16.39
Coke/Her Sales	32.05	31.64	33.35
Coke/Her Possession	25.68	93.20	74.10*
Marijuana Sales	25.67	25.39	26.55
Marijuana Possession	205.91	205.82	206.18
Drunkenness	151.37	136.95	196.61*

* - the mean of the NIBRS counties is significantly different from the mean of the counties not included in the NIBRS.