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

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Abstract

In response to growing abuse of prescription opioid painkillers, 50 U.S. states have implemented electronic prescription drug monitoring programs (PDMPs) that record patients into a state-wide registry when a prescription opioid is received. This paper uses a difference-in-differences regression framework and interactive fixed effects factor models to identify the effect of PDMPs and two related programs on the types and strengths of opioid painkiller prescriptions filled and on rates of heroin crimes. The implementation of PDMP databases caused an 8% decrease in the amount of oxycodone shipments, with results from Medicaid prescription data pointing to larger decreases within high dosage pills. PDMPs have heterogeneous effects on heroin crime incidents across counties depending on the county's pre-policy level of prescription opioid milligrams per capita, with an 87% increase in heroin crime within the most 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] Skyrocketing overdose deaths have surpassed fatal car accidents as the leading cause of accidental death and have contributed to the recent

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

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 implementation 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. First, I provide evidence that PDMPs significantly decrease access to strong prescription opioids. 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 25%, which is driven by a 35% 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

[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.

capita. While PDMPs don't have significant effects on heroin crime rates in the aggregate, they increase the rate of heroin crime incidents by 87% 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. Opioid molecules bind to opioid receptors in the body, relieving pain and sometimes creating a feeling of relaxation, well-being, or euphoria. Opioids also slow breathing and heart rate, sometimes to the point of respiratory failure in the event of an overdose. 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]

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 to prescribers as safe and non-habit-forming due to its slow-release mechanism which prevented a sudden high and crash cycle that fosters withdrawal and dependence. OxyContin was also unique because of Purdue Pharmaceutical's aggressive marketing approach, which heralded massive revenue growth from $48 million in 1996 to $3.1 billion in 2012. Purdue painted Oxycontin as a miracle drug for the common American with chronic, non-cancer pain. Other opioid-producers followed suit, and the marketing was so effective that a medical field formerly characterized by "opiaphobia" that sometimes went so far as to deny opioid treatment to terminally ill patients now considers 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]

OxyContin contains the active ingredient oxycodone and pills range anywhere from a low dose of 10 milligrams to a high dose of 80 milligrams (as well as the now-discontinued 160 milligram pill). The continuous-release mechanism of the pill was a patented wax coating, but determined opioid abusers could dissolve away the coating or crush the pills into powder in order to swallow, snort, smoke or inject a large immediate hit of the morphine-like drug.

[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.

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

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, which realized 87 million opioid prescriptions.

2.2 Prescription Drug Monitoring Programs

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 establisment 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. Many states began data collection 1-12 months before prescribers could access the electronic PDMPs, creating a possible announcement effect.[5]

Due to low prescriber use of the PDMPs, 12 states[6] implemented usage mandates on top of existing non-mandated PDMPs that require prescribers to query the PDMPs under certain circumstances. In addition, eight states[7] 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.[8] 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.

[5]Dates were obtained by searching the internet for effective dates of electronic, online PDMPs by state. Most dates were verified using several sources, including news articles, the Prescription Drug Monitoring Program Training and Technical Assistance Center website, the National Alliance for Model State Drug Laws website, state legislative laws and bills, government newsletters, various articles from peer reviewed journals, and pharmacy board websites.

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

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

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

2.3 Substitution to Heroin

Heroin and opioids are nearly identical at the chemical level[9] and produce similar effects in the body, acting as powerful pain suppressants and creating feelings of wellbeing and euphoria in large doses. Ways of taking heroin have changed, with an increasing prevalence for smoking and snorting because drug purity is now so high that injecting is not required for an intense euphoria. 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). The heroin of the 2010s is produced in Mexico and South America, is often nearly 100% pure, and costs $10 for a small 10 milligram capsule filled with white powder. Disconcertingly, to improve potency most heroin is now laced with a strong synthetic opioid called fentanyl, which is 50-100 times stronger than morphine. Inconsistent amounts of fentanyl (or yet-more-potent fentanyl analogs) within heroin doses is the cause of many unexpected overdoses.

According to the Center for Disease Control, only 3% of prescription opioid abusers initiate heroin abuse, but 75-80% of heroin users report that they transitioned from abusing prescription drugs. Partially due to the prevalence of users who transition from opioids to heroin, the opioid crisis is now a socio-demographically wide-spread phenomenon, with the most concentrated effects among white non-Hispanic Americans (Cicero et al., 2014). In contrast, past drug crises like the heroin crisis of the 1970s and the crack epidemic of the 1980s and 1990s had been concentrated among urban and minority populations. Prescription opioid overdoses increased in the 2000s among middle-aged non-Hispanic white Americans, and heroin and fentanyl overdoses skyrocketed in the 2010s among non-Hispanic white Americans between ages 20 and 35 (Unick and Ciccarone, 2017). The opioid crisis is also geographically widespread, affecting suburban and rural areas nationwide.

The 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 and Power, 2017; Kilby, 2015; Meinhofer, 2017). This paper is unique among these in that I link non-mandated PDMPs to heroin transition, use heroin crime rates rather than heroin overdose deaths or treatment admissions as a measure of heroin abuse, and perform my heroin analysis at the county level instead of the usual coarser state level, with an emphasis on heterogeneous effects of the policy on heroin transition in different types of counties.

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

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).[10] Few studies that examine the 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, likely 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.[11] 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. Several recent studies find significant effects of PDMP usage mandates that require doctors to check already-existent 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.

[10] 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 (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.

[11] 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 economics literature has also begun to connect opioid abuse and heroin-substitution outcomes. Studies by Alpert et al. (2017) and Evans and Power (2017) 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 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.[12] 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

[12] 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[13] 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 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 table is divided into non-Medicaid respondents and Medicaid-enrolled respondents. I further divided the data into all respondents, and respondents who report having ever used hydrocodone non-medically, used oxycodone non-medically, and used OxyContin non-medically. Hydrocodone, oxycodone, and OxyContin are presented in ascending order of potency and abuse potential. Hydrocodone is a relatively weak Schedule III opioid typically prescribed for acute temporary pain, and oxycodone is a stronger Schedule II substance used to treat moderate to severe chronic pain. Most opioid crackdowns have focused on limiting oxycodone. About a third (0.348) of oxycodone abusers report having used OxyContin, the slow-release formulation of oxycodone that comes in large doses.

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

Within the survey, Medicaid respondents are more likely to abuse opioids; and among groups of hydrocodone, oxycodone and OxyContin abusers, Medicaid enrollees use opioids more frequently than their non-Medicaid counterparts. The first column lists summary statistics for the entire Non-Medicaid and Medicaid subsets of the data, including respondents who do not abuse opioids. 11% of survey respondents not on Medicaid report having ever abused opioids, and the average respondent in the non-Medicaid group reports abusing opioids 2.029 times in the past year. Within the respondents who are Medicaid enrollees, 12.7% have ever abused opioids and the average respondent has abused opioids 3.30 times in the past year. The second column restricts both the Non-Medicaid and Medicaid groups to those who reported having ever abused hydrocodone. The average non-Medicaid abuser of hydrocodone has misused opioids 20.19 times in the past year, compared to 28.89 abuses for the average Medicaid counterpart. Abusers of oxycodone and OxyContin show the highest rates of reported abuse: oxycodone abusers report misusing opioids 22.82 and 32.41 times a year, in the non-Medicaid and Medicaid subsets respectively, and OxyContin abusers report using 40.45 and 52.10 times respectively. Medicaid have both higher rates and frequencies of reported heroin abuse than the non-Medicaid respondents. Those who abuse hydrocodone, oxycodone and OxyContin are much more likely to report heroin use as well, with increasing odds (8.4%, 11.4%, and 19.7% in the non-Medicaid population, and 10.8%, 14.6% and 23.4% in the Medicaid-enrolled population) across opioid-strength categories.

Since Medicaid enrollees are more likely to abuse opioids than the general population, and abuse increases across drug-strength categories, the Medicaid dataset used for this paper is advantageous in revealing the true effects of the PDMP. I expect PDMPs disproportionately affect heavy-abusers of opioids, so the Medicaid population provides a good chance of finding large and significant policy effects.

Medicaid tracks the universe of prescriptions the program pays for and compiles the information into aggregated reports on the Medicaid website in the Medicaid State Drug Utilization Data. The Medicaid dataset on opioid pills covers 7-15% of all prescription painkillers in the United States. The National Drug Code (NDC) is a unique product-identifier that identifies each drug by its manufacturer, active ingredient, and dosage amount, among other details. The Medicaid data report the state-by-quarter counts of each NDC prescribed. I use the NDC to merge the Medicaid data to detailed information from the Food and Drug Administration.[14] For my analysis, I restrict my observations to tablets[15]

[14]Many of the NDCs for opioids found in the Medicaid data are outdated, so I manually searched for records by NDC and obtained dosage and strength information on outdated NDCs from many different websites.

[15]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 oxycodone and hydrocodone painkillers, the most commonly abused opioids. Patients typically receive take-home opioid prescriptions in the form of tablets.[16]

Because the Medicaid data are reported at the NDC level, I aggregate milligrams by both drug type and strength, differentiating drug milligrams that come in the form of low-dose pills from those in high-dose pills. Opioid active ingredients have varying potencies, so I use different milligram cutoffs for hydrocodone and oxycodone drugs. Oxycodone is 1.5 times as strong as hydrocodone. I define a low-dose pill as a hydrocodone pill with 15 or fewer milligrams of hydrocodone or an oxycodone pill with 10 or fewer milligrams of oxycodone. A high-dose oxycodone pill contains greater than 10 milligrams of oxycodone, and a high-dose hydrocodone pill contains more than 15 milligrams of hydrocodone. Hydrocodone is typically not found in pills with more than 15 milligrams.[17] The 10 milligrams oxycodone/15 milligrams hydrocodone cutoffs were chosen because commonly-abused Percocet and Vicodin have 10 or fewer oxycodone milligrams and 15 or fewer hydrocodone milligrams, respectively. More dangerous pills like OxyContin, whose abusers exhibit more severe abuse characteristics, have more than 10 milligrams of oxycodone.[18]

3.2 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. I use the shipped quantites of oxycodone and hydrocodone between 2000 and 2014 to supplement my Medicaid results with data from the general population, as well as for comparison to other studies in the literature that also use the ARCOS (Kilby, 2015; Reisman et al., 2009). The ARCOS data provides more fine-grained geographical information at the zipcode and county level than dos the Medicaid data, which is at the state level. I use ARCOS county oxycodone per capita to obtain a proxy measurement for pre-policy opioid abuse within counties. 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.

of codeine, a relatively weak form of opioid.

[16]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.

[17]In the Medicaid data, only 0.2% of hydrocodone comes in higher-dose, extended release capsules.

[18]Effects disaggregated on pill strength are robust to using different milligram cutoffs for "strong" pill classification. Results are driven by 30, 40, and 80 mg oxycodone pills, as covered in Appendix C.

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[19] 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.

3.3 NIBRS

The National Incident-Based Reporting System (NIBRS) is an incident-level dataset of crimes committed in 6,251 law-enforcement jurisdictions across 38 states and 1,634 counties. For the purpose of this paper, I use a 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 drug crimes involving the purchase, sale or possession of heroin or illegally obtained prescription opiates. I collapse the NIBRS incident-level data to obtain a panel of the 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 their density of oxycodone, revealed by the ARCOS data, for the year 2004, prior to the timing of most electronic PDMPs. My rationale is that PDMPs

[19] I classify capsules and tablets as tablets.

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. I proxy the number of existing opioid abusers with the recorded numbers of oxycodone milligrams per capita, matching zipcode-level ARCOS data to county-level crime data in order to obtain fine geographic measures of oxycodone density. I use each county's mean per-quarter amount of oxycodone per capita in 2004 to proxy the initial stock of opioid abusers susceptible to the PDMP. The 2004 level is late enough that the opioid crisis was beginning to affect counties differently, but early enough that most PDMPs had not been implemented. 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 of oxycodone density, at 63.15 milligrams of oxycodone per capita. The 10% of counties that are above this cutoff are the "high oxycodone density" counties and the bottom 90% that are more centered around 25 mg/capita are classified as "low oxycodone density" counties.[20] Figure 3 shows oxycodone-density for the counties in the NIBRS data, 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 the lower 655 (counties that make up the bottom 90%) of the oxycodone-per-capita distribution, and crime rates within the 80 counties (counties that make up the top 10%) with the highest oxycodone-per-capita. The typical county realizes 1.3 heroin incidents and 2.2 incidents of illegally diverted opioids per 100,000 population per month. The less oxycodone-dense counties experience a mean of 1.124 heroin incidents and 1.866 diverted-opioid incidents per month, whereas the highly-opioid-dense counties experience 2.342 and 4.009 heroin and diverted-opioid incidents, respectively. Thus, the rates in the most oxycodone-dense counties are twice as high.

To identify possible heroin dealers in the NIBRS dataset, I count the individuals per county and month who 1.) are carrying more than 2 grams[21] of heroin, 2.) Are carrying between 1 and 2 grams of heroin and a large amount of another drug[22], or 3.) Are carrying

[20]Results are robust to different cutoffs. Appendix B includes figures that plot coefficient estimates when using cutoffs other than the 90th percentile, and suggest that the heroin results are significant among the top 30% of counties in terms of oxycodone density.

[21]1 gram of heroin is 100 doses of 10 mg each. States have varying levels of heroin amounts that create the assumption of "trafficking," with Idaho, Maine, Mississippi, South Carolina, and Vermont considering 2 grams an important cutoff for trafficking, assigning harsher punishments to those carrying above 2 grams of heroin. Other states typically have cutoffs ranging between 1 and 5 grams, but laws differ drastically across states.

[22]More than 1 gram of crack cocaine, more than 1 gram of cocaine, more than 500 grams of marijuana

any heroin and were entered in the data as selling any drug. A probable opiate dealer is someone who 1.) is carrying more than 5 grams or 250 pills of opiates, 2.) is carrying between 2 and 5 grams or between 100 and 250 pills and are carrying a large amount of another drug, or 3.) is carrying opiates and are entered as selling any drug.

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. This approach identifies changes in trends within the treated geographies that correspond to the timing of the implementation of the policy. I adapt the difference-in-differences models into an event-study framework with policy lags and leads to test the parallel trends assumption. I later supplement the analysis with interactive fixed effects factor models (IFE), as detailed in Bai (2009), which are explained later in the paper.

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

(about 17 oz–enough to be charged with a felony in most states), more than 2 grams of opioids, or more than 1 gram of methamphetamine.

population in state i in quarter t or earlier.[23] $PDMP_{it}$ is an indicator that is equal to one if state i has established an electronic Prescription Drug Monitoring Program by quarter t. $Mandate_{it}$ is an indicator equal to one if a state has mandated that prescribers must check the PDMP under certain circumstances by time period t. $PillMillBill_{it}$ is an indicator equal to one if a state has passed a menu of laws targeting "Pill Mills."[24] γ_t is a set of time period fixed effects that flexibly capture the average national time path of the outcome variable. ι_i is a set of geography fixed effects that control for the average level of the outcome variable in a state and the effects of time-invariant state characteristics. ϵ_{it} is a stochastic, normally distributed error term.

Event-study graphs (for example, graphs in Figures 4 and 5) 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.[25] 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 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 Table 5. 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

[23]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.

[24]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.

[25]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.

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.[26] I control for state-varying Medicaid expansion under the Affordable Care Act, but the expansion occurs in 2014, 2015, and 2016 and is not driving results.[27]

Finally, I control for effects of the abuse-deterrent reformulation of OxyContin that became prevalent in 2010, because Alpert et al. (2017) and Evans and Power (2017) 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 and Power, 2017). Their models control for heterogeneous effects of the reformulation across different states by multiplying a post-reformulation indicator variable by the pre-reformulation proxy for opioid abuse. Similarly, I control for differing effects of the reformulation across states by multiplying a post-reformulation indicator by a state's mean number of OxyContin milligrams per Medicaid enrollee (in the Medicaid data) in 2004.[28]

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.[29,30] $PDMP_{ct}$, $Mandate_{ct}$, 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

[26]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.

[27]Regressions dropping data from 2013-2015 yield similar results, meaning the ACA is not driving coefficient estimates. Results available upon request.

[28]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.

[29]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.

[30]The NIBRS includes a variable that lists each reporting jurisdiction's covered population. Jurisdiction populations within the same county are summed when aggregated to the county level.

fixed effects.

Table 6 lists county controls in matrix X_{ct}. Controls 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.[31] I adapt the approach in Alpert et al. (2017) and Evans and Power (2017) 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.[32]

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):

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

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.

4.3 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

[31] 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.

[32] 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 and Power (2017), 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 (measured by NSDUH OxyContin abuse reports) on heroin abuse (measured by heroin overdoses).

(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).

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

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.

5 Results

5.1 Effect of the PDMP on Prescription Amounts

Table 7 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 hyrocodone amounts per capita. The model specification in Table 7 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)). 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, respectively.

The Medicaid outcome variables in Columns (1) through (4) are in logged morphine milligrams per Medicaid enrollee and the ARCOS outcome variables in Columns (5) and (6) are in logged morphine milligrams per capita, meaning that table entries are interpreted as proportional increases and decreases in the dependent variable in response to the PDMP, Mandates, and "Pill Mill Bills." Column (1) shows the PDMP reduces Medicaid oxycodone per Medicaid enrollee by 24.6%, which is significant at the 10% level. Column (2) shows neither a large nor significant reduction in oxycodone per Medicaid enrollee in the form of weak-dose ($\leq$10mg) oxycodone pills; however, Column (3) shows a significant 35% reduction in strong-dose (>10mg) oxycodone per Medicaid enrollee in response to the PDMP. In Column (5), the PDMP is found to reduce the aggregate amount of oxycodone shipped per capita by 8%, significant at the 10% level. Neither Columns (4) nor (6) suggest that the PDMP has an effect on hydrocodone use. See Appendix A for Medicaid prescription results across model specifications.

Figure 4 shows the accompanying event study graphs for the weighted difference-in-differences model in Columns (1), (2), and (3) from Table 7, in which the dependent variables are Medicaid total oxycodone, weak oxycodone, and strong oxycodone per enrollee. The vertical line in each graph marks the first quarter of the PDMP. Oxycodone begins trending downward at the time of the policy implementation, and this effect is driven by a reduction in strong oxycodone, which makes up the majority of all oxycodone amounts dispensed through Medicaid. The leads of the oxycodone and strong oxycodone graphs are close to zero until the policy takes effect at quarter zero, which supports the parallel trends assumption. The states with PDMPs had similar growth paths to states without PDMPs prior to the implementation of the policy. The parallel trends assumption seems to hold. The graphs show a break in

trend among the treated states at the time of the policy implementation, lending evidence to the PDMP causing a decrease in oxycodone.

Figure 5 plots the event study coefficient of the model on aggregate shipment rates of oxycodone from the ARCOS data, and shows an 8% 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 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. The CDC states that people enrolled in Medicaid are more prone to opioid and heroin abuse (see Table 2), meaning that if PDMPs affect all opioid abusers similarly, the effect will be greater in the Medicaid data because opioid abusers make up a larger fraction of the Medicaid population (Frank, 1999). Additionally, prescribers who interact with high-abuse populations are more likely to use a PDMP, even if it is not mandated (Goodin et al. (2012), Ross-Degnan et al. (2004), and Irvine et al. (2014)), so in areas with large abuse populations, PDMPs are perhaps effective in cutting usage despite not being mandated by law. In short, the Medicaid population may be specially positioned for the PDMP to work well on it.

Although many of the models in Table 7 show significant effects of the Mandate and Pill Mill Bill policies on drug amounts, all of the event study models fail the parallel trends assumption, and are not remedied by the addition of trends. Both Mandate and Pill Mill Bill results on prescription outcomes are volatile across model specifications.[33]

A novel contribution of this study is that I find the decrease Medicaid-prescribed oxycodone is driven by reductions in prescriptions for the high-dosage oxycodone pills (¿10mg). No other study has considered heterogeneous effects of the PDMP on oxycodone drugs of differing strengths. For additional detail, Appendix C includes an analysis of the PDMP effect on Medicaid oxycodone at a further level of disaggregation, and it finds that reductions in the 30, 40, and 80 milligram pills are driving the overall reduction in strong-dose pills. I also find that PDMP reductions among Medicaid prescriptions are only prevalent among generic oxycodone pills, and not brand-name OxyContin.[34]

[33]See Appendix A for model estimates and graphs of Mandate event studies. This paper is restricted to examining 12 Mandates passed between 2007 and 2015. Since 2015, 15 more states have passed and or implemented Mandates to their PDMPs, and future work on the effectiveness of Mandates may benefit from the additional states.

[34]Hwang et al. (2015) and Meinhofer (2016) 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 8 shows the effect of the PDMP on crime incidents in which heroin is seized per 100,000 NIBRS-covered population in a county and month. Entries in this table show the effect of the PDMP, Mandate and "Pill Mill Bills" on number of heroin crime incidents per 100,000 population. These entries interpretable as the change in heroin crime incidents per 100,000 per month caused by the policies. 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).

Panel A shows the effect of the policies across all counties in the NIBRS. Column (1) shows coefficient estimates from a simple ordinary least squares model of the heroin crime rate on the PDMP, Mandate and Pill Mill Bill. The significant estimate of 0.466 shows that PDMP-instigation is positively correlated with the rate of heroin incidents. This correlation is likely due to an overall upward trend in heroin incidents over time. Column (2) adds county and time fixed effects to the OLS specification, controlling for county levels and a national average trend in heroin incidents, and the point estimate falls to 0.155 additional heroin incidents after the passage of the policy, and this result is statistically insignificant. Column (3) adds county demographic and economic controls (as summarized in Table 6), and estimates do not substantially change from the fixed effects specification in Column (2). Column (4) adds county-specific time trends, and estimates become larger in magnitude (0.384) but remain insignificantly different from zero. Column (5) applies the IFE factor model, as outlined in Section 4.3, which nests difference-in-differences and time trends while controlling for unobserved confounding variables at the county level. The positive estimate and statistical significance of the factor model's estimate in Column (5) suggests there is some meaningful heterogeneity not being addressed in the difference-in-differences approach at the national level. However, this is only significant at the 10% level and demands confirmation, which will be given below.

As in the state-level models on prescription outcomes, the results for the Mandate and Pill Mill Bill effects on crime rates are volatile across model specifications. In Panels B and C in Table 8, Mandate effects on heroin incidents switch signs between the control and linear-time-trend model specifications. This is likely because the effect of the Mandate within the NIBRS-covered counties is identified using changes in the policy across only 8 states. The results for Pill Mill Bills also vary dramatically across specifications, likely because effects are identified using 6 treated states in the NIBRS data. The small sample sizes of too few treated states could be confusing results.

Panel B in Table 8 shows that the PDMP has an insignificant effect on the rate of heroin incidents in counties that had a low oxycodone density prior to the policy, and are therefore

likely to be less susceptible to the policy. The IFE factor model finds a small significant increase (0.095 additional heroin incidents per 100,000 people per month) in the rate of heroin incidents among the bottom 90% of counties, equal to an 11% increase. Since the difference-in-differences estimates and the IFE factor model estimates are not consistent with one another, it is not certain that there was a change in heroin incidents in the less oxycodone-dense counties. Appendix B shows insignificant, near-zero effects of the PDMP in the bottom half of counties by oxycodone density when the more oxycodone-dense half of counties are excluded from the model.

In contrast to the less oxycodone-dense counties, the counties in the top 10% of the distribution, as shown in Panel C of Table 8, experience a statistically significant effect of 1.745, 1.69 or 0.972 additional heroin incidents per 100,000 population per month under the specifations with controls and linear time trends, and the IFE factor model specificatio, respectively. Police are encountering 47% to 84% more heroin incidents in these highly susceptible counties, which experience a baseline of 2.07 heroin incidents per 100,000 NIBRS-covered population per month in the year prior to the policy. This large, positive effect of the PDMP in high-density counties is robust across many different estimation specifications.[35]

Figure 6 shows the effect over time of the PDMP on the rate of heroin incidents in all counties in the top graph, and in the counties with high oxycodone density in the bottom graph. The event study graphs contain dashed vertical lines that allow for a possible announcement effect during a six month window leading up to the effective date of the policy.[36] Consistent with Panels A and C of Table 8, the graphs show an increase 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. Post-implementation, the graph line trends upwards, meaning PMDP is causing more heroin incidents in the counties with the highest oxycodone shipments per capita.

Table 9 contains estimated effects of the policies 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 8). Again, Panels A-C distinguish types of counties by oxycodone density. Columns (1) through (4) document model coefficient estimates on the rates of heroin

[35]This result is robust to the removal of analytic weights, though somewhat less precise. This result is also robust in poisson regressions and in the context of weighted and unweighted factor models, and results from all models are available upon request.

[36]Many states began documenting controlled substances in the PDMP system months before the PDMP was accessible by prescribers (the effective date of the policy), perhaps resulting in a slight announcement effect.

incidents (taken from Table 8), 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 37% increase from the pre-policy, pre-announcement level of 0.880.

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.[37] 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 84% increase in heroin incidents in the most susceptible areas, equal to about 1.75 additional incidents per 100,000 population per month, consistent with predictions.[38]

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, often 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. 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. 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.

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

[37] As shown in Panel C of Table 8 and discussed further Appendix B, the effect of the PDMP on heroin outcomes is driven by those counties in the top half of the oxycodone-per-capita distribution.

[38] The 84% increase estimate is obtained from the analytic-weighted difference-in-differences model with county and month fixed effects and controls. The result that the PDMP causes a large increase in heroin incidents in the most opioid-dense counties is robust across model specifications, including additional difference-in-differences specifications, factor model specifications, and a Poisson framework, all available upon request to the author.

not surprising in light of the uncertain theoretical predictions.

5.3 Results from the Interactive Fixed Effects Factor Model

As explained in section 4.3, the IFE factor model from Bai (2009) flexibly accounts for nationwide time trends that affect different counties based on unobservable characteristics. Results calculated from the difference-in-differences models and IFE factor model are similar in regressions on prescription outcomes (as seen in Appendix A), 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, and Figure 9 graphs a polynomial fit of the nationwide trend in race of heroin incidents by county. Difference-in-differences models are able to pick up this non-linear common time trend in the figure by including time fixed effects. The nationwide time trends in Figure 9 does not account for differences in time trends across counties.

Figure 10 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, with a sudden acceleration after 2010. During time periods 0 through 80, which corresponds to the period 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.[39] Controlling for a level shift allows the abuse-deterrent reformulation to affect counties proportional to their likely abuse exposure. However, it appears that controlling for the reformulation in this way 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.[40] Figure 11 contains a map of the NIBRS counties' Factor 1 loadings. The darkest-color counties in

[39] Alpert et al. (2017) and Evans and Power (2017) use a similar method.

[40] 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.

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 fit lines to their heroin incident rates over time. Figure 12 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 dramatic increase in the 2010s. Figure 13 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. A linear trend fit to Spotsylvania's heroin incidents will provide a poor fit, and it biases the coefficient estimates of the PDMP upward.[41] The counties with large factor 1 loadings experience a sharp increase in heroin incidents in later time periods, and the difference-in-differences models with linear time trends will fit linear trends to counties partially based on the shallower slope in heroin incidents between 2004 and 2010. The increase in heroin incidents after 2010 will fall above the trend, and may be falsely attributed to the PDMP.

Table 10 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 very close to the IFE factor model estimates (0.112) because the county-specific polynomials capture the curvature in heroin incidents within counties.

6 Additional Robustness Checks

6.1 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,

[41] Virginia's PDMP was implemented in June 2016, corresponding to time period 30 and South Carolina's PDMP was implemented in June 2008, corresponding to time period 55.

ARCOS oxycodone, and heroin incidents among oxycodone-dense counties.

Table 11 displays rejection rates from a placebo test as suggested in Bertrand et al. (2004). Concerns about autocorrelation are especially pertinent to difference-in-differences regressions on addictive opioid drugs, which have a highly correlated temporal pattern. Using the state-quarter Medicaid data and county-month crime rate data, I randomly assign fake PDMP, Mandate and Pill Mill Bill laws to states for any time between 2004 and 2014, with probability equal to the relative frequency of the real policies in the data. I then run my models on the data with the placebo policies to test rejection rates. Fictitious placebo laws should be significant at the 5% level 5% of the time. Table 11 shows that difference-in-differences over-rejects the null hypothesis of zero effect for all policies, to varying degrees. The problem is most acute for the Mandate policy and the Pill Mill Bill regulation, with 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).[42] P-values obtained from this procedure are included in brackets for key results in Table 7, Table 8 and Table 9. IFE factor model results are cluster-bootstrapped as well.

7 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 25% reduction in oxycodone prescribed, which is driven by an even larger 35% decrease in high-

[42]This procedure involves taking the residuals of a model run without the independent variables of interest (in my case, the PDMP, Mandate and Pill Mill Bill) and randomly reassigning them within treated clusters. The residual randomization disrupts the autocorrelation in the error term within clusters that causes over-rejection of the null. The procedure then runs the difference-in-differences regression model on the data with the randomly-ordered residuals, and, bearing similarities to a placebo test, obtains a distribution of t-statistics under the meaningless data. The real t-statistic is compared to the distribution of bootstrapped t-statistics and is assigned a p-value equal to its percentile within the distribution.

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 47% to 84% 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.

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

State	PDMP Date	Mandate Date	"Pill Mill" Bill Date
Alaska	January 2012		
Alabama	August 2007		
Arkansas	March 2013		
Arizona	December 2008		
California	July 2009		
Colorado	February 2008		
Connecticut	July 2008		
Delaware	August 2012	March 2012	
Florida	October 2011		July 2011
Georgia	July 2013		
Hawaii	January 1982		
Iowa	March 2009		
Idaho	July 2008		
Illinois	Janurary 2008		
Indiana	July 2008		
Kansas	April 2011		
Kentucky	March 2005	July 2012	July 2011
Louisiana	January 2009	August 2014	July 2005
Massachusetts	December 2010	June 2013	
Maryland	January 2014		
Maine	January 2005		
Michigan	March 2011		
Minnesota	April 2010		
Missouri	July 2017		
Mississippi	March 2011		September 2011
Montana	October 2012		
North Carolina	October 2008		
North Dakota	January 2007		
Nebraska	April 2011		
New Hampshire	October 2014		
New Jersey	January 2012		
New Mexico	August 2005	September 2012	
Nevada	October 2004	October 2007	
New York	August 2013	August 2013	
Ohio	October 2006	November 2011	May 2011
Oklahoma	July 2006		
Oregon	September 2011		
Pennsylvania	August 2016		
Rhode Island	September 2012		
South Carolina	June 2008		
South Dakota	March 2012		
Tennessee	December 2006	January 2013	January 2012
Texas	August 2012		June 2009
Utah	January 2006		
Virginia	June 2006		
Vermont	April 2009	November 2013	
Washington	January 2012		
Wisconsin	May 2013		
West Virginia	January 2004	June 2012	September 2014
Wyoming	July 2004		

Dates obtained from the National Alliance for Model State Drug Laws, Brandeis University's Prescription Drug Monitoring Program Training and Technical Assistance Center, state legislative laws and bills, government newsletters, news articles, articles from peer reviewed journals, and pharmacy board websites.

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	0.110	1	1	1
Past Year Frequency Opioids	2.029	20.190	22.822	40.453
Fraction Abused Heroin	0.011	0.084	0.114	0.197
Past Year Frequency Heroin	0.174	1.766	2.426	5.616
Fraction Abused Hydrocodone	0.077	1	0.663	0.897
Fraction Abused Oxycodone	0.056	0.481	1	1
Fraction Abused OxyContin	0.019	0.226	0.348	1
Observations	915,123	70,637	51,222	17,837
Medicaid Population				
Fraction Abused Opioids	0.127	1	1	1
Past Year Frequency Opioids	3.303	28.889	32.41	52.100
Fraction Abused Heroin	0.015	0.108	0.146	0.234
Past Year Frequency Heroin	0.289	2.636	3.847	7.143
Fraction Abused Hydrocodone	0.078	1	0.688	0.879
Fraction Abused Oxycodone	0.057	0.503	1	1
Fraction Abused OxyContin	0.022	0.257	0.400	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: 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 6: 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.

Table 7: The Effect of Policies on Logged Prescription Amounts per Capita

	Medicaid Data				ARCOS Data	
	(1) Oxycodone	(2) Weak Oxycodone	(3) Strong Oxycodone	(4) Hydrocodone	(5) Oxycodone	(6) Hydrocodone
PDMP	-0.246*	-0.0813	-0.350**	-0.0530	-0.0814*	-0.0041
	(0.128)	(0.146)	(0.151)	(0.146)	(0.135)	(0.0263)
	[0.087]	[0.286]	[0.033]	[0.359]	[0.065]	[0.519]
Mandate	0.342**	-0.247	0.344***	-0.208*	0.157**	-0.165***
	(0.145)	(0.164)	(0.145)	(0.184)	(0.0589)	(0.0390)
	[0.989]	[0.844]	[0.992]	[0.123]	[0.99]	[0.001]
Pill Mill Bill	-0.190	-0.238	-0.185	0.0843	-0.176**	-0.0129
	(0.156)	(0.110)	(0.173)	(0.192)	(0.101)	(0.0506)
	[0.283]	[0.422]	[0.188]	[0.653]	[0.028]	[0.558]
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 8: 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***	0.155	0.239	0.384	0.112*
	(0.0382)	(0.230)	(0.288)	(0.361)	(0.059)
			[0.654]		[0.058]
Mandate	3.774***	1.337	0.945	0.0919	0.123
	(0.226)	(1.050)	(0.666)	(0.251)	(0.308)
			[0.881]		[0.689]
Pill Mill Bill	-1.597***	-0.519	-0.271	0.169	0.111
	(0.181)	(0.867)	(0.702)	(0.230)	(0.312)
			[0.365]		[0.722]
Observations	92292	92292	92292	92292	92292
Panel B: Bottom 90% of Oxycodone Density Counties					
PDMP	0.672***	-0.0767	-0.0306	-0.0256	0.095**
	(0.0359)	(0.0700)	(0.110)	(0.0889)	(0.045)
			[0.236]		[0.036]
Mandate	1.689***	0.178	-0.167	0.0674	-0.023
	(0.202)	(0.822)	(0.623)	(0.278)	(0.137)
			[0.449]		[0.869]
Pill Mill Bill	0.623***	0.752	0.976	0.333*	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	1.249	1.745*	1.690**	0.972***
	(0.139)	(0.821)	(0.795)	(0.745)	(0.303)
			[0.915]		[0.001]
Mandate	5.545***	2.386*	1.115***	-0.497	2.003***
	(0.312)	(1.062)	(0.327)	(0.413)	(0.661)
			[0.999]		[0.002]
Pill Mill Bill	-6.104***	-3.189**	-1.928*	-0.606	-1.174**
	(0.301)	(1.295)	(0.858)	(0.726)	(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 9: The Effect of the PDMP on Drug Crimes Per Capita

	Heroin		Opiates	
	Incidents	Possible Dealers	Incidents	Possible Dealers
Panel A: All 735 Counties				
PDMP	0.239	0.013	-0.162	-0.0174
	(0.288)	(0.0672)	(0.0956)	(0.0257)
	[0.654]	[0.430]	[0.243]	[0.246]
Mandate	0.945	0.160*	0.147	0.0781
	(0.106)	(1.050)	(0.195)	(0.0685)
	[0.881]	[0.925]	[0.589]	[0.721]
Pill Mill Bill	-0.271	-0.231*	-0.325	-0.124
	(0.702)	(0.110)	(0.344)	(0.0639)
	[0.365]	[0.062]	[0.622]	[0.385]
Observations	24780	24384	24384	24384
Panel B: Low Oxycodone Density Counties				
PDMP	-0.031	-0.0317	-0.651	0.014
	(0.288)	(0.0483)	(0.0774)	(0.0248)
	[0.236]	[0.237]	[0.441]	[0.514]
Mandate	-0.167	-0.224	0.437**	0.224**
	(0.623)	(0.136)	(0.347)	(0.0964)
	[0.449]	[0.257]	[0.983]	[0.964]
Pill Mill Bill	0.976	0.111	-0.284	-0.222
	(0.763)	(0.127)	(0.476)	(0.0911)
	[0.794]	[0.688]	[0.674]	[0.515]
Observations	21096	20964	20964	20964
Panel C: High Oxycodone Density Counties				
PDMP	1.745*	0.324*	-0.547	-0.248
	(0.795)	(0.140)	(0.213)	(0.0971)
	[0.915]	[0.918]	[0.131]	[0.150]
Mandate	1.115***	0.374**	-0.378	-0.237
	(0.327)	(1.050)	(0.208)	(0.103)
	[0.999]	[0.978]	[0.139]	[0.204]
Pill Mill Bill	-1.597**	-0.601**	-1.160*	-0.465*
	(0.181)	(0.235)	(0.249)	(0.329)
	[0.026]	[0.010]	[0.078]	[0.096]
Observations	3684	3420	3420	3420

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ 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.

Table 10: 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	0.239	0.384	0.108	0.112*	0.138**
	(0.228)	(0.361)	(0.081)	(0.059)	(0.057)
Mandate	0.945	0.092	-0.036	0.123	0.485
	(0.666)	(0.666)	(0.143)	(0.308)	(0.402)
PillMill	-0.271	0.169	-0.036	0.111	0.114
	(0.702)	(0.230)	(0.131)	(0.312)	(0.461)
Observations	92292	92292	92292	92292	92292
Panel B: Top 10% Oxycodone Density Counties					
PDMP	1.745*	1.690**	0.412	0.927***	0.949***
	(0.795)	(0.745)	(0.496)	(0.303)	(0.304)
Mandate	1.115**	-0.497	-0.097	1.990***	2.003***
	(0.327)	(0.413)	(0.311)	(0.664)	(.661)
PillMill	-1.928*	-0.606	-0.598	-1.154***	-1.174***
	(0.858)	(0.726)	(0.383)	(0.547)	(0.551)
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.

Table 11: Rejection Rates Under Placebo Test at 5% Level

Policy:	PDMP	Mandate	Pill Mill Bill
Medicaid and ARCOS Prescription Outcomes			
Medicaid Oxycodone	0.084	0.163	0.321
Medicaid Weak Oxycodone	0.118	0.236	0.352
Medicaid Strong Oxycodone	0.079	0.160	0.315
Medicaid Hydrocodone	0.137	0.227	0.389
ARCOS Oxycodone	0.058	0.155	0.317
ARCOS Hydrocodone	0.147	0.222	0.360
Drug Crime Outcomes			
Heroin Incidents	0.089	0.150	0.389
Heroin Dealers	0.083	0.119	0.334
Opiate Incidents	0.303	0.123	0.349
Opiate Dealers	0.091	0.082	0.380

The PDMP, Mandate, and Pill Mill Bill dates were randomly reassigned to take effect in a pre-PDMP time period. The prescription regression model run includes state and quarter fixed effects, controls, Medicaid enrollment weights and linear time trends. The drug crime regression models include county and month fixed effects and controls, and dont include county trends. Rejection rates are from regression models using cluster robust weighting.

Table 12: Weighted Poisson Regression: Effect of PDMP on Prescription Outcomes

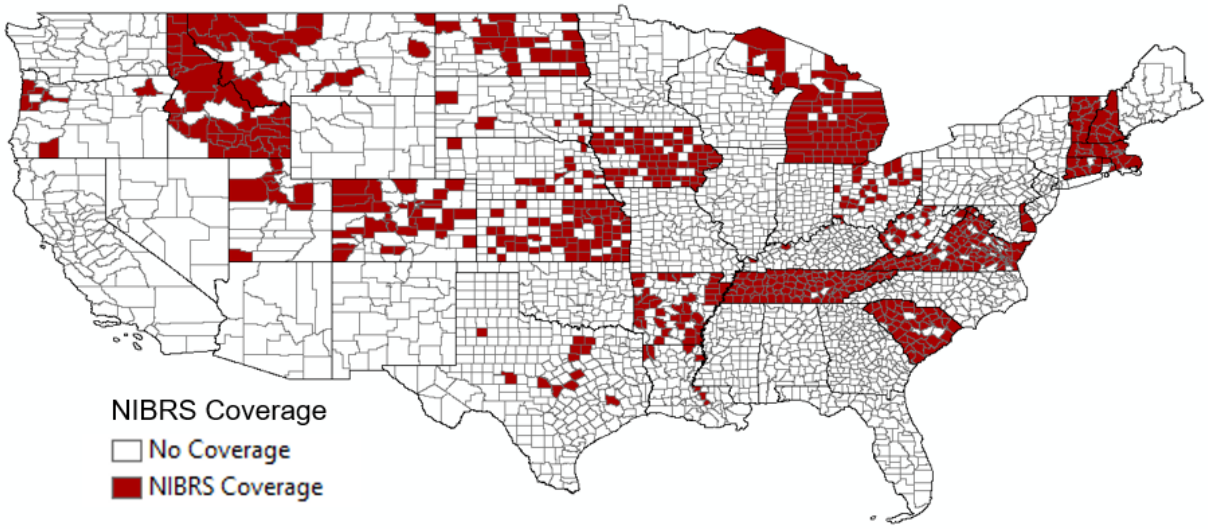
	Med Oxy	Med Weak Oxy	Med Strong Oxy	ARCOS Oxy
PDMP	-0.212***	-0.074***	-0.275***	-0.084**
	(0.058)	(0.024)	(0.073)	(0.029)
Mandate	-0.239*	-0.304**	-0.148	-0.052
	(0.134)	(0.135)	(0.118)	(0.037)
Pill Mill Bill	0.079	0.064	0.026	-0.051
	(0.110)	(0.073)	(0.109)	(0.122)
Observations	3070	3070	3070	3070

Table 13: Poisson Regression: Effect of PDMP on Heroin Incidents

	Count	Rate per 100,000
Panel A: All Counties		
PDMP	0.123*	0.1833**
	(0.086)	(0.092)
Mandate	-0.047	0.070
	(0.104)	(0.138)
Pill Mill Bill	0.051	0.326
	(0.212)	(0.277)
Observations	67,092	66,948
Panel B: Top 10% Oxycodone Dense Counties		
PDMP	0.231**	0.380
	(0.118)	(0.278)
Mandate	0.131	0.497***
	(0.093)	(0.164)
Pill Mill Bill	-0.450	-0.734**
	(0.277)	(0.301)
Observations	8,088	8,076

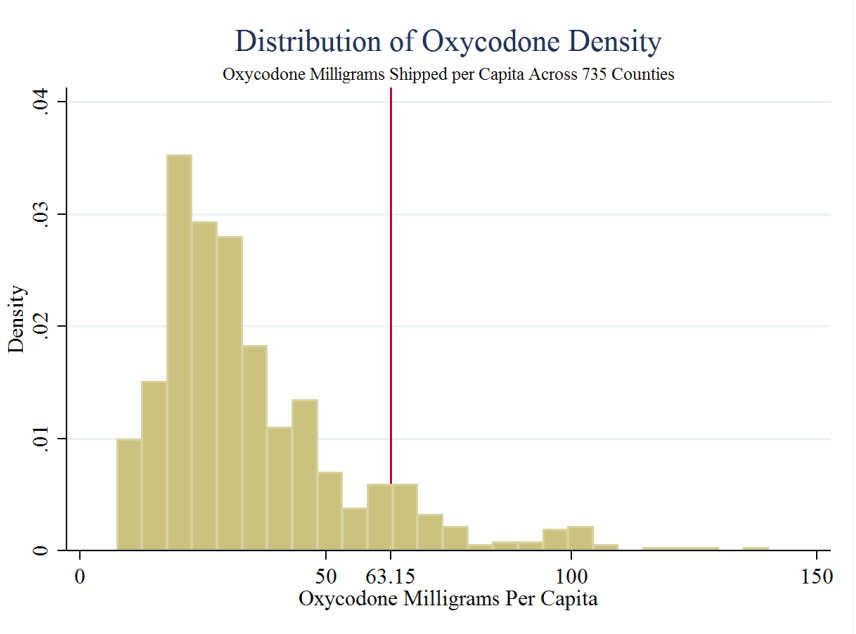
Robust errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: A Map of NIBRS Data Coverage



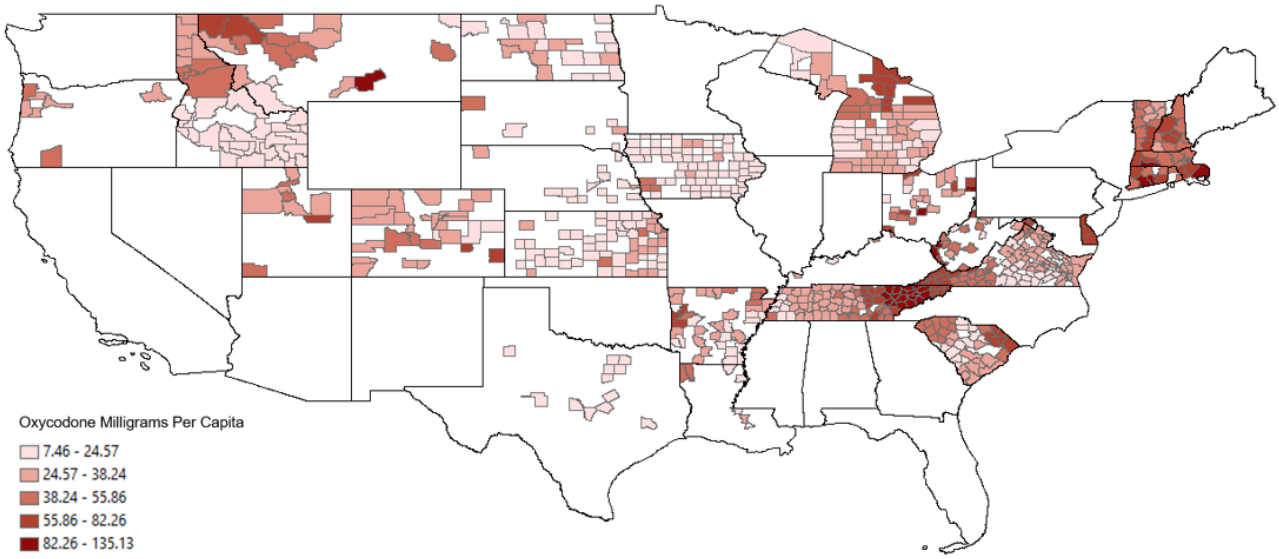
Notes:The map shows the 735 counties for which there exists a complete monthly panel dataset of counts of crimes from 2004 to 2014 within the NIBRS dataset.

Figure 2: The Distribution of Oxycodone Per Capita Across Counties



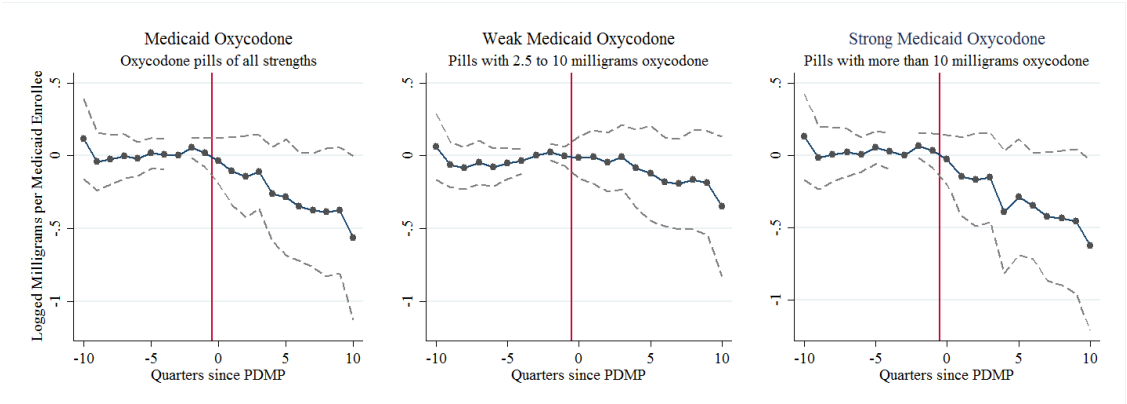
Notes: The figure plots the distribution of 2004 oxycodone density across 735 counties. The top 10% most oxycodone dense counties have greater than 63.15 milligrams of oxycodone per capita per month, equivalent to 6-12 weak dose pills or 2-3 strong dose pills per month for each resident. The PDMP has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

Figure 3: NIBRS County Oxycodone Density



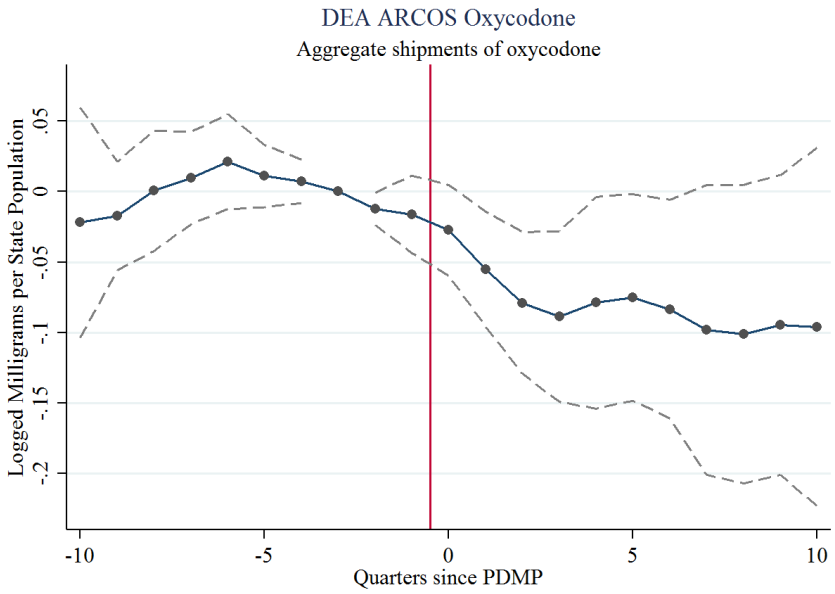
The figure displays the NIBRS-covered counties colored by oxycodone milligrams per person. Darker counties are more oxycodone dense. Oxycodone density data: DEA ARCOS.

Figure 4: PDMP on Medicaid Oxycodone Outcomes Over Time



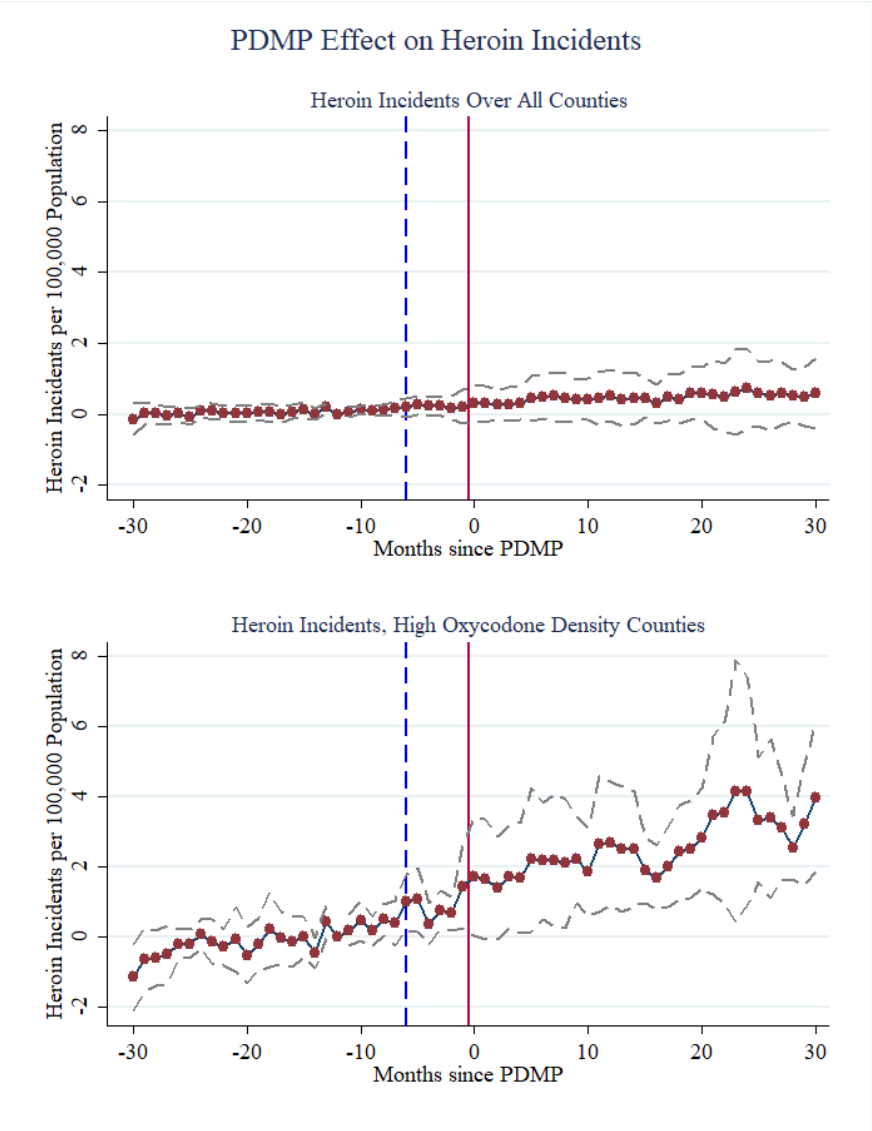
Notes: The figures plot coefficients on lag and lead policy indicators from difference-in-differences models on logged amounts of oxycodone by Medicaid prescriptions (milligrams per capita). The dependent variable is restricted to weak dose oxycodone in the center graph and strong dose oxycodone in the right graph. The graphs correspond to event-study adaptations of Columns (1), (2) and (3) of Table 7 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 5: PDMP on Aggregate Oxycodone Shipments



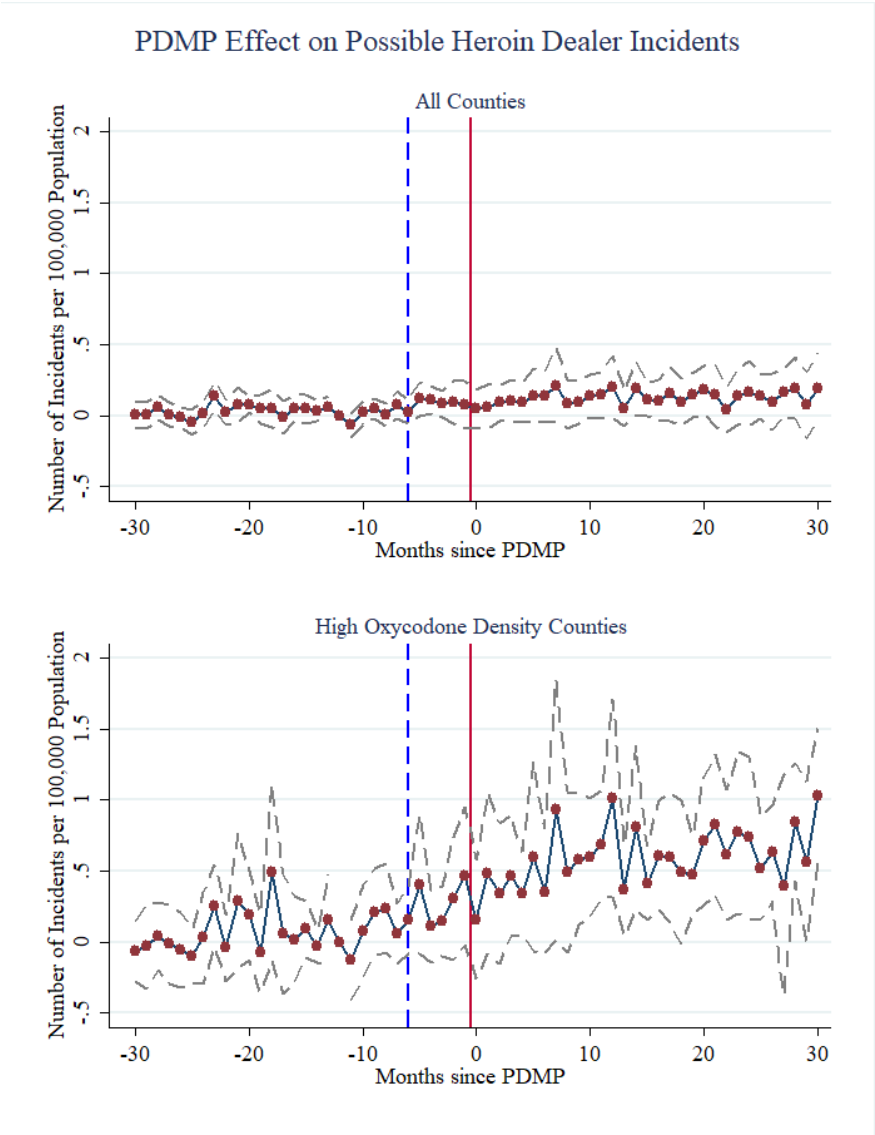
Notes: Same as Figure 4, except using aggregate shipments of oxycodone from ARCOS. The trends graphs correspond to Column (5) of Table 7 and includes state and time fixed effects, controls, population weights, and state-specific linear time trends. The dataset spans 50 states plus the District of Columbia quarterly from 2000-2015. Aggregate Shipment Data: DEA ARCOS

Figure 6: PDMP on Heroin Incidents Over Time



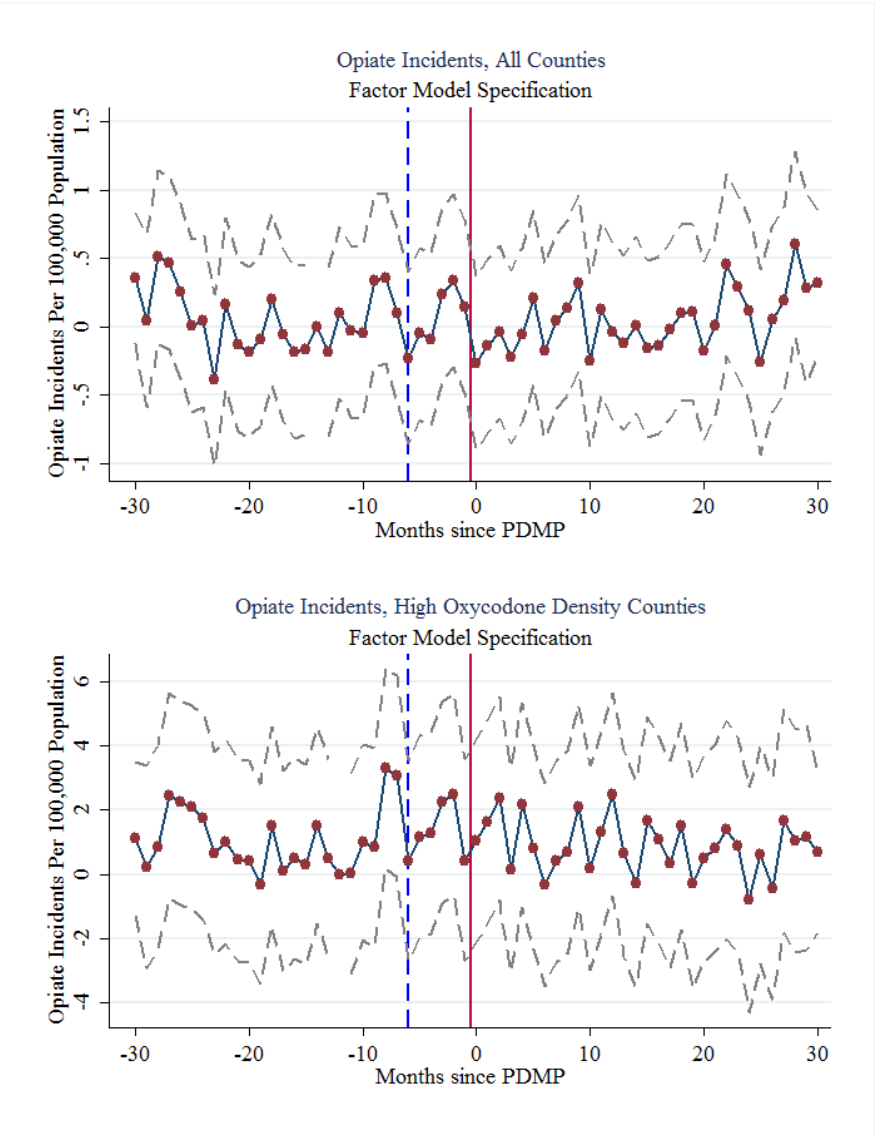
Notes: Graphs plot the coefficients on PDMP lags and leads indicators in a difference-in-differences regression on heroin incidents per 100,000 in a county-month pair. The top graph shows the event study of the PDMP on heroin incidents across all counties. The lower graph shows the event study of the PDMP 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



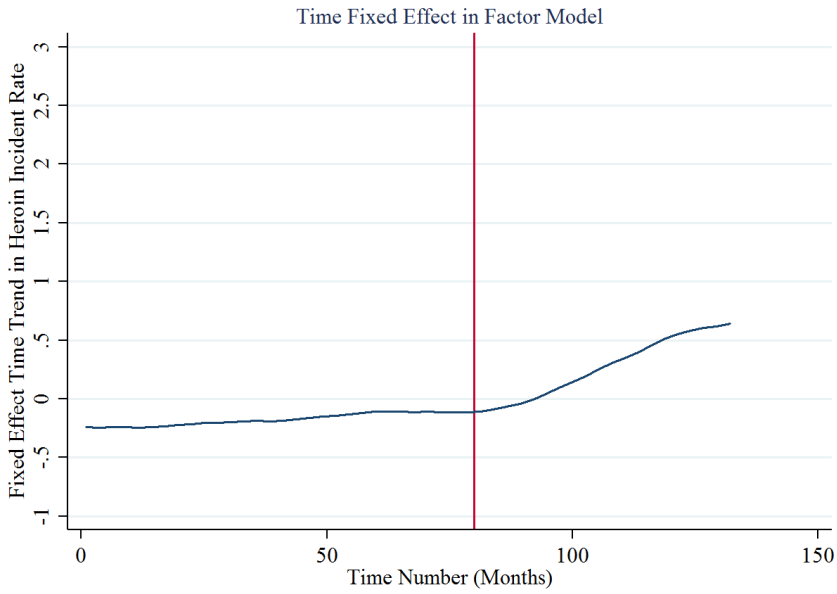
The event study graphs plot the effect of the PDMP on the rate over time of incidents involving possible heroin dealers in all counties and in counties with high oxycodone density. A possible heroin dealer incident is one where individuals 1.) are carrying more than 2 grams of heroin, 2.) Are carrying 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



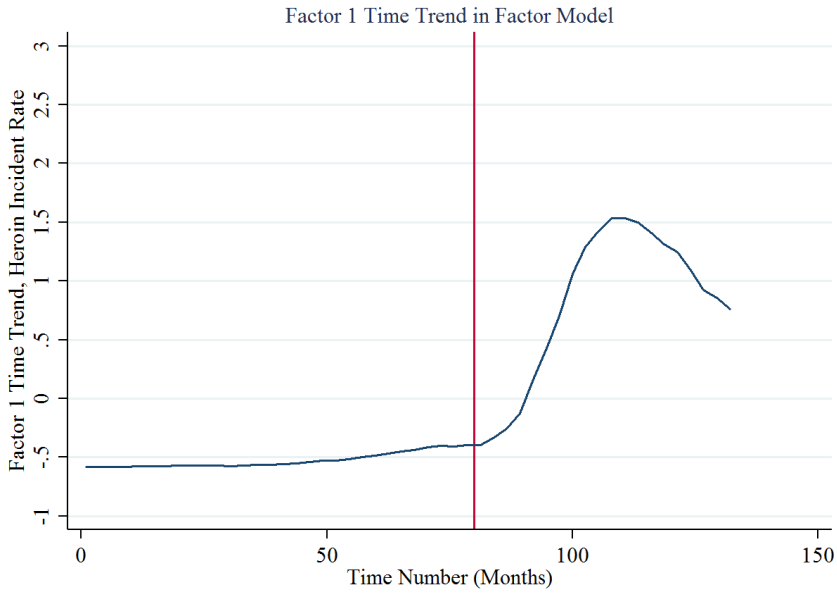
The graphs display the event study of the PDMP on Opiate Incidents per 100,000 population. The factor model is used because difference-in-differences specifications do not pass the parallel trends test, due to non-linear county-specific time trends that are captured using the factor model.

Figure 9: The Nationwide Time Trend in Heroin Incidents, Obtained from the IFE Factor Model



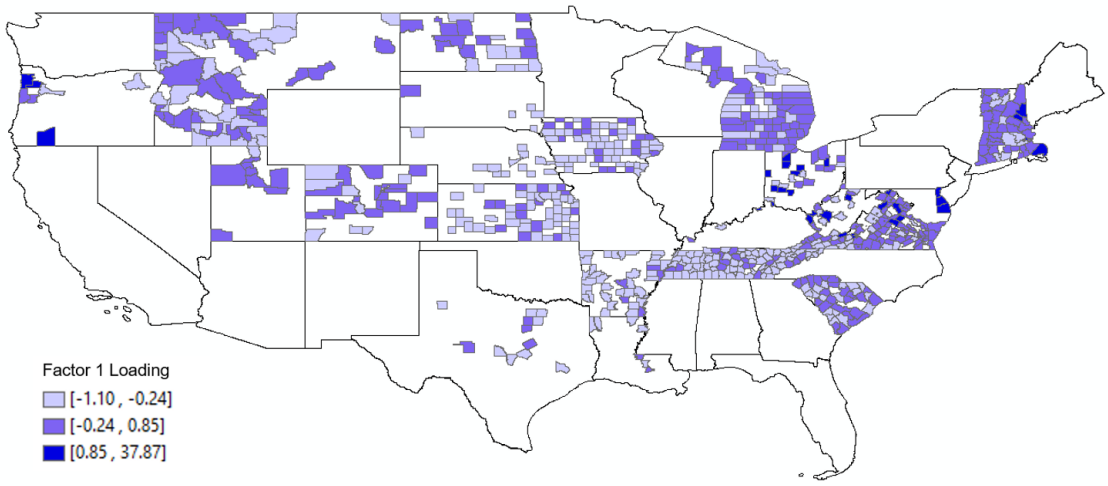
Notes: The figure shows the average time trend (time fixed effects) in the heroin incident rate from the IFE factor model. Heroin incident data: NIBRS.

Figure 10: Factor 1 From the Interactive Fixed Effect Factor Model on Heroin Incident Rate



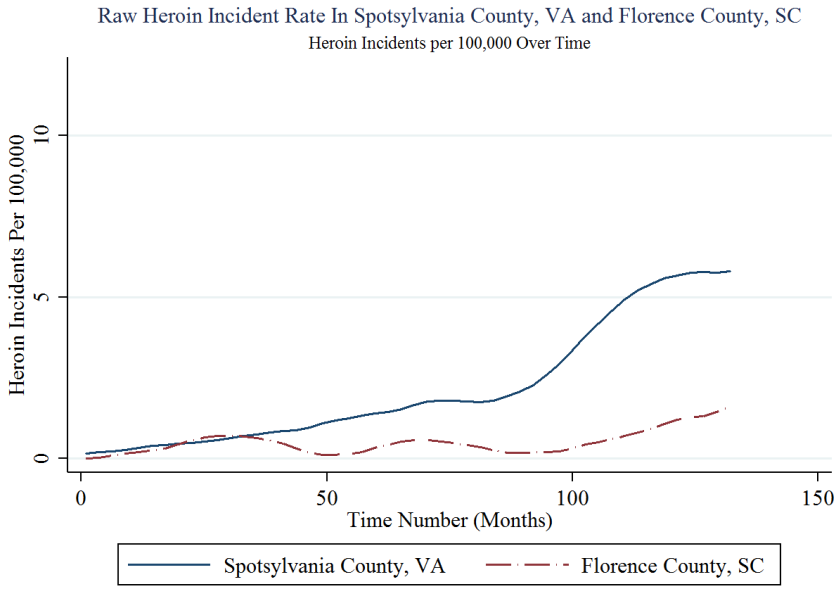
Notes: The graph plots the IFE factor model's factor 1 time trend. The red line marks the OxyContin reformulation that made it harder to abuse. Within the IFE factor model, Factor 1 is the time trend that accounts for the most residual variance.

Figure 11: Counties by Factor 1 Loadings



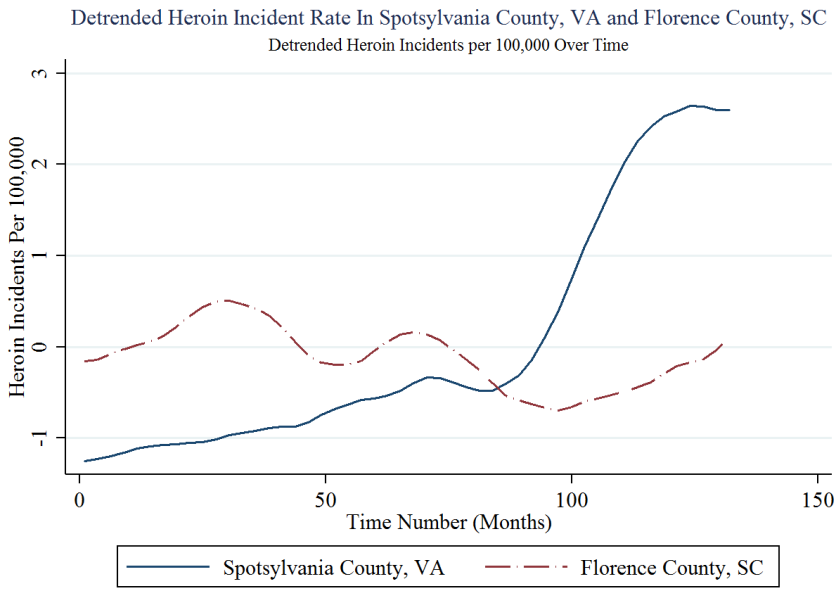
Notes: The map displays counties from the NIBRS data colored by each county's sensitivity to the Factor 1 time path from the interactive fixed effects factor model as shown in Figure 10. Factor 1 seems to pick up differences in county responses to the OxyContin reformulation, and the dark-colored counties perhaps have exceptional sensitivity to the reformulation.

Figure 12: Heroin Incident Rate in Two Example Counties



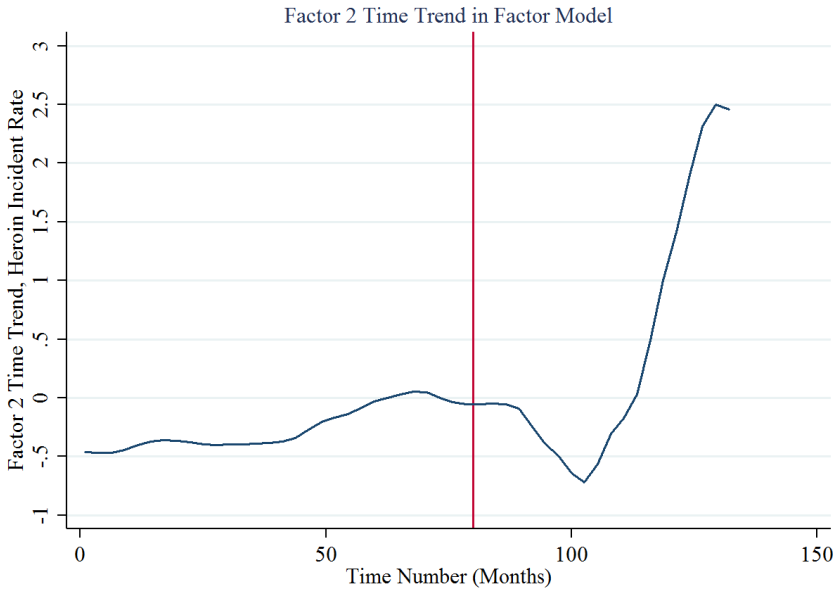
Notes: The graph compares the raw heroin incident rate over time in 2 counties with approximately 100,000 population. Spotsylvania County, VA is assigned a high factor 1 loading and Florence County, SC is assigned an average factor 1 loading under the IFE factor model. The factor 1 time trend captures a non-linear increase in the heroin incident rate over time, as seen in Figure 10, and Spotsylvania County's data corresponds with factor 1's more dramatic exponential growth in the heroin incident rate over time.

Figure 13: 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.

Figure 14: Factor 2 From the Interactive Fixed Effect Factor Model on Heroin Incident Rate



The figure plots the second factor from the IFE factor model on the rate of heroin incidents. The red line marks the reformulation of OxyContin, which made it harder to abuse. Time periods 100-105 correspond to April to October 2012.

Appendix A Additional Robustness and Model Specifications: Prescription Outcomes

Tables A1, A2, A3, A4, A5, and A6 list the effects of the PDMP, Mandate and Pill Mill Bills on Medicaid oxycodone, Medicaid weak oxycodone, Medicaid strong oxycodone, Medicaid hydrocodone, ARCOS oxycodone, and ARCOS hydrocodone usage, respectively, under different model specifications. In each table, the specifications include simple ordinary least squares in Column (1) in each of the tables, then the addition of fixed effects, controls, and linear time trends in Columns (2) through (4). Column (5) in each table drops analytic weights from the models, Column (6) drops data past 2012 to eliminate any possible confounding influences posed by the implementation of the Affordable Care Act, Column (7) excludes Florida (the state that was considered the "pill mill capital" of the US in the 2000s) from the model, and Column (8) lists coefficients from the interactive fixed effects factor model applied to prescription outcomes. Results are fairly consistent across model specifications, with Medicaid oxycodone, strong oxycodone, and ARCOS oxycodone responding to the policies across specification. However, PDMP estimates lose both power and magnitude when Florida is excluded from models, although magnitudes of coefficients are still negative. Results of the PDMP on heroin incidents in the NIBRS do not use Florida for identification.

Turning to the Mandate policy, Figure A1 graphs its effects on prescription outcomes under a difference-in-differences specifications with fixed effects and controls but not including state-specific linear time trends. Non-zero lead coefficients characterize all six graphs, which is a problem. The addition of linear time trends does not bring the lead coefficients to zero. Therefore each of the graphs in Figure A1 suggest a violation of the parallel trends assumption required for causal inference in difference-in-differences models. As the lead coefficients are statistically significantly different from zero, the treated counties did not trend similarly to untreated counties in the time prior to the mandate. Because of this failure of the parallel trends assumption, I cannot draw causal inferences regarding the effects of the Mandates on outcomes.

Table A1: PDMP on Log Medicaid Oxycodone Across Model Specifications

	(1) OLS	(2) FE	(3) Controls	(4) LTT	(5) NoWt	(6) NoACA	(7) DropFL	(8) Factor
PDMP	-0.257***	-0.223	-0.246*	-0.188	-0.236	-0.221	-0.116	-0.148*
	(0.0413)	(0.160)	(0.128)	(0.144)	(0.152)	(0.147)	(0.142)	(0.0858)
Mandate	0.915***	0.431**	0.342**	0.141	0.133	0.133	0.0718	0.217
	(0.111)	(0.170)	(0.145)	(0.153)	(0.278)	(0.134)	(0.143)	(0.141)
Pill Mill Bill	-0.666***	-0.366*	-0.190	-0.186	0.0258	-0.118	-0.0589	-0.031
	(0.131)	(0.206)	(0.154)	(0.165)	(0.223)	(0.152)	(0.160)	(0.253)
Observations	2791	2791	2783	2783	2783	2582	2727	2714
Fixed Effects		X	X	X	X	X	X	X
Controls			X	X	X	X	X	X
Linear Trends				X	X	X	X	$\hbar$
Weights	X	X	X	X		X	X	
Drop 2014 on						X		
Drop Florida							X	
Factor Model								X

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\hbar$: The interactive fixed effects factor model flexibly nests time trends.

Table A2: PDMP on Log Medicaid Weak Dose Oxycodone, Across Model Specifications

	(1) OLS	(2) FE	(3) Controls	(4) LTT	(5) NoWt	(6) NoACA	(7) DropFL	(8) Factor
PDMP	-0.289***	-0.0438	-0.0813	-0.0341	-0.0760	-0.0523	-0.0240	-0.050
	(0.0417)	(0.167)	(0.146)	(0.153)	(0.171)	(0.163)	(0.147)	(0.047)
Mandate	-0.253***	-0.348**	-0.350**	-0.247	-0.282*	-0.300*	-0.160	0.0891
	(0.165)	(0.164)	(0.164)	(0.159)	(0.272)	(0.165)	(0.157)	(0.114)
Pill Mill Bill	-1.042***	-0.359**	-0.115	-0.0462	-0.00389	-0.0132	-0.0307	-0.007
	(0.174)	(0.158)	(0.110)	(0.137)	(0.190)	(0.119)	(0.159)	(0.177)
Observations	2790	2790	2782	2782	2782	2581	2726	2713
Fixed Effects		X	X	X	X	X	X	X
Controls			X	X	X	X	X	X
Linear Trends				X	X	X	X	$\hbar$
Weights	X	X	X	X		X	X	
Drop 2014 on						X		
Drop Florida							X	
Factor Model								X

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\hbar$: The interactive fixed effects factor model flexibly nests time trends.

Table A3: PDMP on Log Medicaid Strong Dose Oxycodone, Across Model Specifications

	(1) OLS	(2) FE	(3) Controls	(4) LTT	(5) NoWt	(6) NoACA	(7) DropFL	(8) Factor
PDMP	-0.253***	-0.348**	-0.350**	-0.247	-0.282*	-0.300*	-0.160	-0.172**
	(0.0417)	(0.167)	(0.146)	(0.153)	(0.171)	(0.163)	(0.147)	(0.077)
Mandate	0.790***	0.409**	0.344**	0.120	0.0807	0.0301	0.0390	0.106
	(0.0953)	(0.177)	(0.145)	(0.155)	(0.234)	(0.145)	(0.138)	(0.166)
Pill Mill Bill	-0.572***	-0.341	-0.238	-0.226	0.110	-0.157	-0.0831	-0.072
	(0.121)	(0.212)	(0.173)	(0.190)	(0.249)	(0.172)	(0.184)	(0.225)
Observations	2766	2766	2758	2758	2758	2557	2702	2692
Fixed Effects		X	X	X	X	X	X	X
Controls			X	X	X	X	X	X
Linear Trends				X	X	X	X	$\hbar$
Weights	X	X	X	X		X	X	
Drop 2014 on						X		
Drop Florida							X	
Factor Model								X

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\hbar$: The interactive fixed effects factor model flexibly nests time trends.

Table A4: PDMP on Log Medicaid Hydrocodone, Across Model Specifications

	(1) OLS	(2) FE	(3) Controls	(4) LTT	(5) NoWt	(6) NoACA	(7) DropFL	(8) Factor
PDMP	0.0833	-0.0740	-0.0530	-0.111	-0.0817	-0.0618	-0.150	0.067
	(0.0544)	(0.216)	(0.135)	(0.115)	(0.101)	(0.107)	(0.111)	(0.090)
Mandate	-0.582**	-0.380	-0.208	-0.308*	-0.297	-0.471*	-0.266	-0.355*
	(0.243)	(0.344)	(0.184)	(0.184)	(0.195)	(0.242)	(0.185)	(0.194)
Pill Mill Bill	-0.0384	-0.187	0.0843	-0.0575	-0.156	-0.0165	-0.160	-0.121
	(0.117)	(0.300)	(0.192)	(0.142)	(0.232)	(0.133)	(0.179)	(0.208)
Observations	2782	2782	2782	2782	2782	2581	2726	2714
Fixed Effects		X	X	X	X	X	X	X
Controls			X	X	X	X	X	X
Linear Trends				X	X	X	X	$\hbar$
Weights	X	X	X	X		X	X	
Drop 2014 on						X		
Drop Florida							X	
Factor Model								X

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\hbar$: The interactive fixed effects factor model flexibly nests time trends.

Table A5: PDMP on Log ARCOS Oxycodone, Across Model Specifications

	(1) OLS	(2) FE	(3) Controls	(4) LTT	(5) NoWt	(6) NoACA	(7) DropFL	(8) Factor
PDMP	0.124***	-0.0894*	-0.0814	-0.0847**	-0.0584**	-0.124**	-0.0256	-0.032*
	(0.0436)	(0.0499)	(0.0509)	(0.0401)	(0.0291)	(0.0510)	(0.0221)	(0.017)
Mandate	0.428***	0.193**	0.157**	-0.0862	-0.0935**	-0.0591	-0.145***	-0.037
	(0.0593)	(0.0785)	(0.0589)	(0.0556)	(0.0445)	(0.0549)	(0.0376)	(0.041)
Pill Mill Bill	-0.197***	-0.290***	-0.276***	-0.210**	-0.115	-0.173	-0.0575	-0.024
	(0.0760)	(0.107)	(0.101)	(0.0970)	(0.117)	(0.105)	(0.0495)	(0.063)
Observations	3264	3264	3153	3153	3153	2594	3090	3070
Fixed Effects		X	X	X	X	X	X	X
Controls			X	X	X	X	X	X
Linear Trends				X	X	X	X	$\hbar$
Weights	X	X	X	X		X	X	
Drop 2014 on						X		
Drop Florida							X	
Factor Model								X

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\hbar$: The interactive fixed effects factor model flexibly nests time trends.

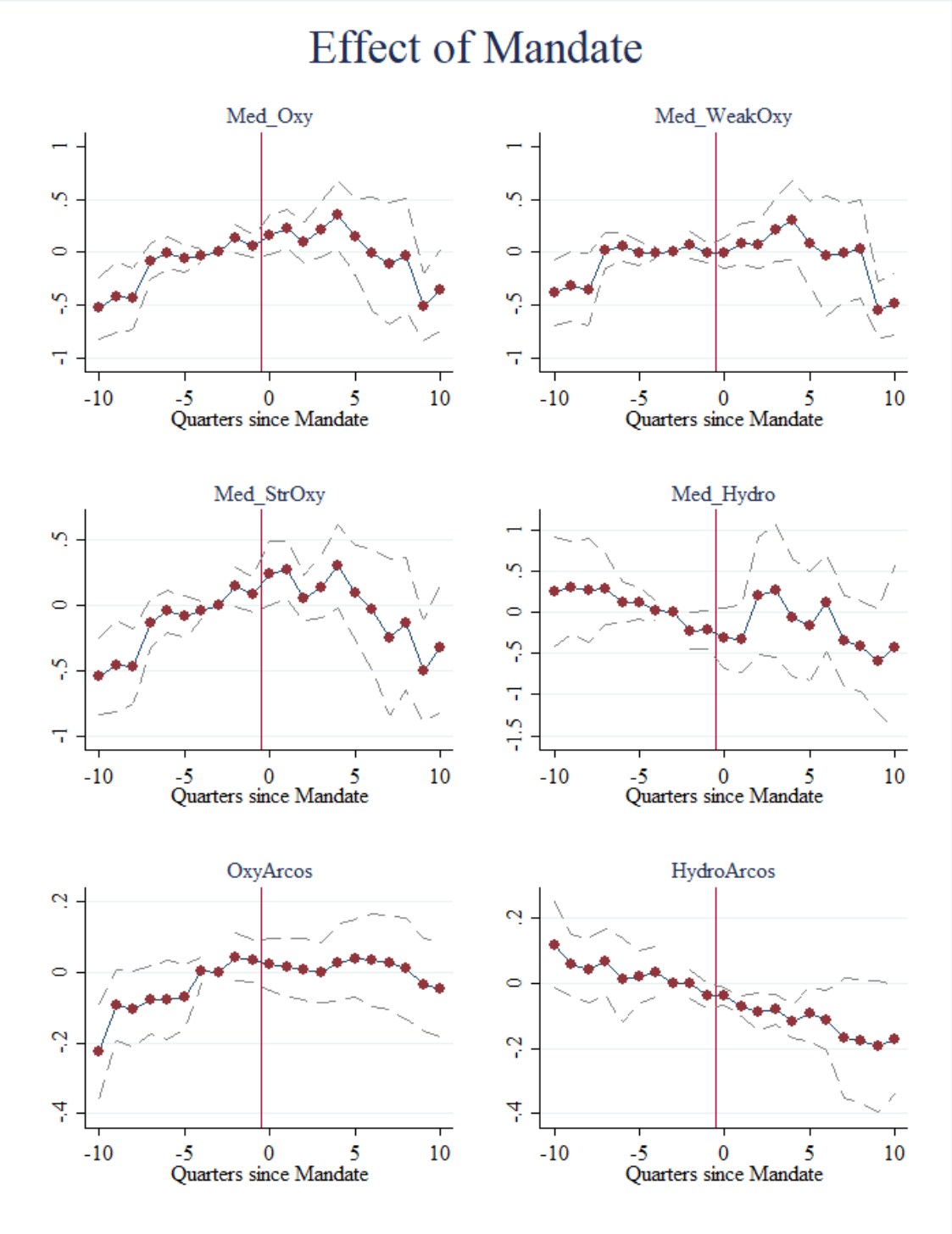
Table A6: PDMP on Log ARCOS Hydrocodone, Across Model Specifications

	(1) OLS	(2) FE	(3) Controls	(4) LTT	(5) NoWt	(6) NoACA	(7) DropFL	(8) Factor
PDMP	0.414***	0.0580	-0.00409	0.0180	0.0264	0.0121	0.0247	-0.021
	(0.0274)	(0.0354)	(0.0263)	(0.0183)	(0.0159)	(0.0200)	(0.0184)	(0.014)
Mandate	-0.372***	-0.148	-0.165***	-0.125***	-0.0905***	-0.0936*	-0.119***	-0.060**
	(0.0735)	(0.0940)	(0.0390)	(0.0355)	(0.0309)	(0.0471)	(0.0345)	(0.028)
Pill Mill Bill	0.534***	0.000350	-0.0129	-0.00830	-0.0198	-0.00362	0.0175	-0.0225
	(0.0561)	(0.102)	(0.0506)	(0.0297)	(0.0298)	(0.0171)	(0.0343)	(0.031)
Observations	3260	3260	3149	3149	3149	2590	3086	3066
Fixed Effects		X	X	X	X	X	X	X
Controls			X	X	X	X	X	X
Linear Trends				X	X	X	X	$\hbar$
Weights	X	X	X	X		X	X	
Drop 2014 on						X		
Drop Florida							X	
Factor Model								X

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\hbar$: The interactive fixed effects factor model flexibly nests time trends.

Figure A1: The Effect of Mandated PDMPs on Medicaid and ARCOS Prescription Outcomes



The graphs display coefficients on Mandate lag and lead indicators in a difference-in-differences model including state and quarter fixed effects and controls, but not including state-specific trends. Note the non-zero lead coefficients.

Appendix B Additional Model Robustness: Heroin Results

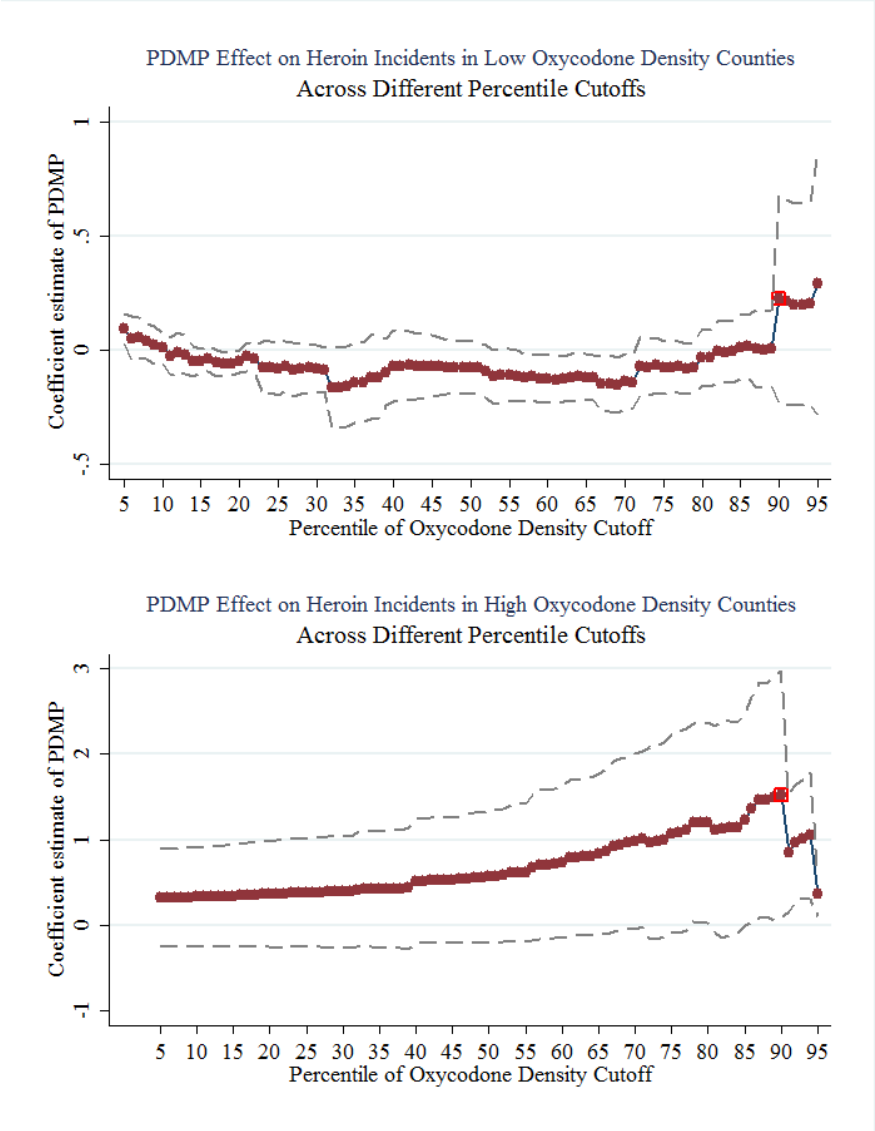
The main text divides counties into "high oxycodone density" and "low oxycodone density" by cutting on the 90th percentile of the distribution of oxycodone per capita. Figure B2 tests the robustness of the significant increase in heroin incidents using different high density and low density cutoffs (other than the 90th percentile). To clarify, the top graph plots policy coefficient estimates on the bottom percentage of counties classified as "low" oxycodone-density counties, with the horizontal axis plotting which percentage cutoff was used to determine which counties were classified as "low" oxycodone-dense counties. The measured effect of the PDMP on the bottom 80-90% (excluding more oxycodone-dense counties) of the data is about zero. The lower graph plots the PDMP effect on heroin incidents within "high" oxycodone-density counties. The PDMP coefficients become significant at the 95% confidence level at about the 70th percentile, so using the top 30% of counties as "high density". These show 1-1.75 additional heroin incidents per 100,000 population each month in the top 30% of oxycodone-dense counties.[43]

Figure B3 tests the robustness of the PDMP effect on heroin incidents on counties with low versus high oxycodone, under the IFE factor model specification. Similarly to Figure B2, the top graph plots coefficients on the bottom 5 through 50 percent of counties cut on oxycodone density, measuring a zero effect of the PDMP. The bottom graph plots the coefficients for IFE factor models run on the top 50 to 95 percent of counties cut on oxycodone density, and measures an increase of 0.2 to 0.6 additional heroin incidents per 100,000 population per month as a result of the PDMP.

Figure B4 plots the event study of the PDMP on heroin incidents across all counties and in the top 10% of counties based on oxycodone-density using the IFE factor model. This graph is the IFE factor model analog to Figure 6 (which plots coefficients from a difference-in-differences model) in the main text. The IFE factor model graphs show similar results to the difference-in-differences graphs in the main text, but display lead coefficient points closer to zero, with less of a possible pre-trend. Figures still display an increase in the heroin incident rate within the most opioid-dense counties after implementation of the PDMP.

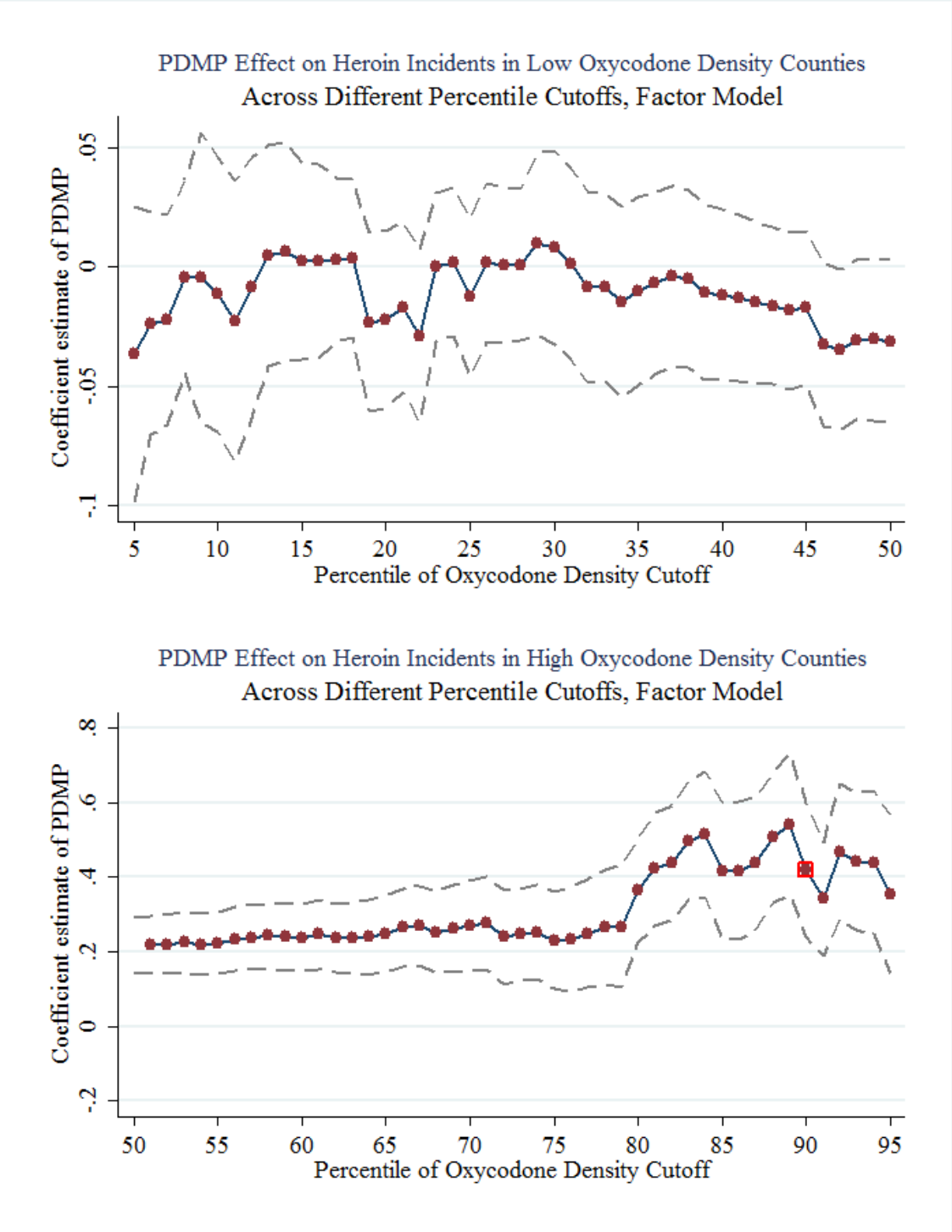
[43] Each plotted point is from a different model run on a different subset of counties in the data, depending on the high/low oxycodone cutoff.

Figure B2: Sensitivity of the Estimated Effects on Heroin Incident Rate Using Different Thresholds to Define High/Low Oxycodone Density Counties



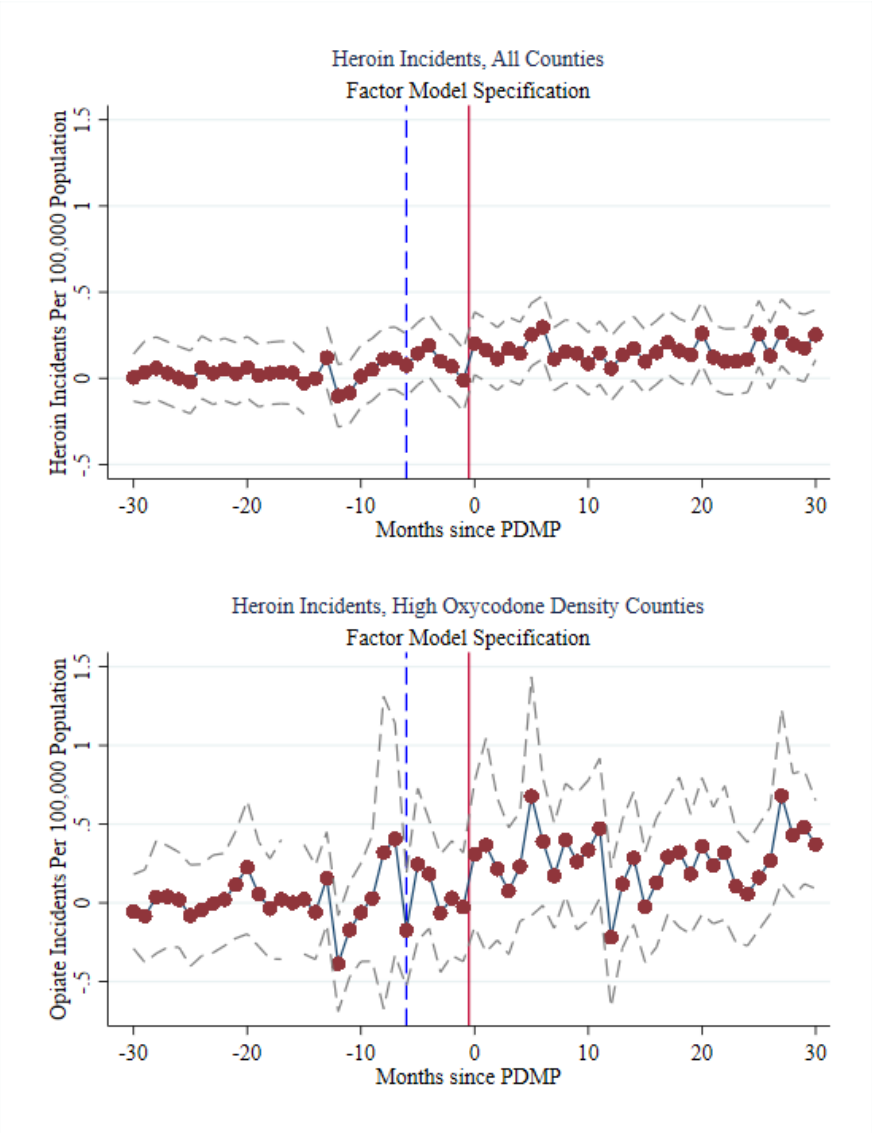
The top figure plots the PDMP estimated coefficients in the less oxycodone dense counties, depending on the threshold (in oxycodone per capita distribution percentile) used to classify counties as "low oxycodone dense" counties. The bottom figure plots the PDMP coefficients for the more oxycodone dense 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.

Figure B3: Sensitivity of the Estimated Effects on Heroin Incident Rate Using Different Thresholds to Define High/Low Oxycodone Density Counties: Unweighted Factor Model



Notes: Graphs plot the coefficients on PDMP lags and leads indicators in an interactive fixed effects factor model on heroin incidents per 100,000 in a county-month pair. The top graph shows the event study of the PDMP on heroin incidents across all counties. The lower graph shows the event study of the PDMP effects in the most oxycodone-dense counties. These event study models include controls and fixed effects by month and county. The county data span 735 counties over 26 states monthly from 2004-2014. Heroin incident data: NIBRS. Oxycodone density data: DEA ARCOS.

Figure B4: The Effect of the PDMP on Heroin Incidents Across All Counties and in Most Oxycodone Dense Counties: Factor Model



Notes: The figure plots event studies of the PDMP on the rate of heroin incidents per 100,000 population per month across all counties (top graph) and across the most oxycodone-dense counties (bottom graph) under the IFE factor model specification.

Appendix C The Effect of PDMPs on Oxycodone by Strength of Pill

The Medicaid drug data comprises state-by-quarter counts of drugs, classified by NDC code. The NDC code specifies the strength of drug by dosage units. Oxycodone comes in pills ranging from 2.5 milligrams to 100 milligrams in the Medicaid data. Table C7 gives summary statistics of oxycodone amounts dispensed through Medicaid, specified by strength of pill. The table lists the mean amount of oxycodone per enrollee by pill strength. It also lists number of pills per enrollee by pill strength. The 5-milligram pills are most common, making up 44.6% of dispensed pills, but only makes up 17.5% of active-ingredient oxycodone dispensed through Medicaid. The 30, 40, and 80 milligram pills make up a small fraction of dispensed pills by number of pills (6.5%, 5.1%, and 3.7% of pills, respectively); however the large-dose pills make up 14.2%, 12.5%, and 17.3% of oxycodone dispensed.

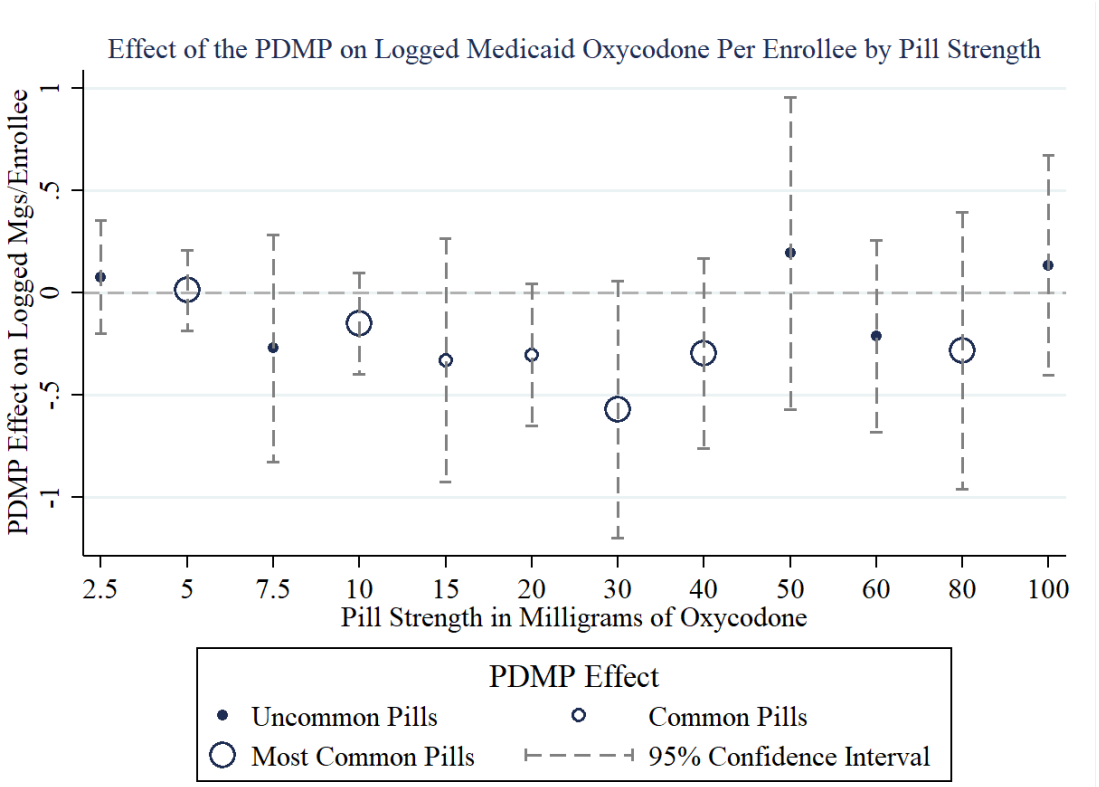
Figure C5 graphs PDMP coefficients from separate difference-in-differences models on logged milligrams of oxycodone per Medicaid enrollee as grouped pills of each strength. The size of each plotted circle is determined by how much of the total dispensed oxycodone comes in each form of pill. The largest circles–associated with 5, 10, 30, 40, and 80 milligram pills–correspond to pills that each make up 10% or more of the oxycodone dispensed, medium-sized points correspond to pills that each make up between 5 and 10% of oxycodone dispensed, and small points are for pills that each make up less than 5% of dispensed oxycodone milligrams. The points are different sizes so that a viewer can determine which pill strengths are most responsible for the aggregated coefficient estimates in Table 7 in the main text. That table shows a 24.6% reduction in overall oxycodone dispensed, and a 35% decrease in strong-dose oxycodone (pills with $>$ 10 milligrams of oxycodone) in response to the PDMP. The large reduction in pills with more than 10 milligrams is driven by large, marginally significant decreases in the prescription rate of oxycodone dispensed in the form of 30, 40, and 80 milligram pills in response to the PDMP.

Table C7: Summary Statistics on Medicaid Oxycodone Pills by Milligrams

Pill Strength	Mean Mg Per Enrollee	Mean Pills Per Enrollee	Fraction of Oxycodone Mg	Fraction of Oxycodone Pills
2.5 mg	0.004	0.0016	0.0001	0.000
	(0.008)	(0.003)		
5 mg	6.14	1.228	0.1746	0.446
	(5.03)	(1.006)		
7.5 mg	1.02	0.137	0.0295	0.052
	(1.14)	(0.153)		
10 mg	5.05	0.505	0.1638	0.218
	(4.70)	(0.470)		
15 mg	2.47	0.164	0.0684	0.0592
	(3.91)	(0.261)		
20 mg	3.05	0.153	0.0775	0.061
	(3.31)	(0.166)		
30 mg	5.10	0.170	0.1421	0.065
	(8.69)	(0.290)		
40 mg	5.41	0.135	0.1248	0.051
	(5.68)	(0.142)		
50 mg	0.356	0.007	0.0113	0.003
	(0.751)	(0.015)		
60 mg	0.760	0.013	0.0223	0.006
	(0.929)	(0.154)		
80 mg	7.29	0.091	0.1727	0.0365
	(7.10)	(0.089)		
100 mg	0.498	0.005	0.0122	0.002
	(1.03)	(0.010)		

Oxycodone comes in pills of varying strength. The table contains summary statistics on the mean milligrams of oxycodone per Medicaid enrollee within each pill strength, the mean number of pills per Medicaid enrollee in each pill strength, the fraction of total Medicaid oxycodone milligrams administered in each pill strength, and the fraction of total oxycodone pills given out in each strength. For example, the average Medicaid enrollee receives 6.14 milligrams of oxycodone in the 5 milligram pill form, equal to 1.228 5-mg-pills per Medicaid enrollee. 5 milligram pills make up 17.5% of oxycodone *milligrams of active ingredient* and 44.6% of oxycodone *pills* covered by Medicaid.
Standard errors are in parentheses. Data source: Medicaid prescription data.

Figure C5: 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, which corresponds to the fraction column in Table C7. "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.

Appendix D The Effect of PDMPs on Heroin Crimes: Offender Characteristics

Results in Table 8 of the main text show that PDMPs increase the rate of heroin incidents in the top 10% of counties in the distribution of oxycodone per capita. The increase of 1.745 additional heroin incidents per 100,000 population per month is equal to an 87% increase. This appendix section uses additional detail from the NIBRS incident-level dataset to identify characteristics of the heroin offenders affected by the policies. The NIBRS dataset shows that at the baseline, the most common locations for heroin incidents are discount and department stores, parking lots and garages, homes and residences, and roads including highways, alleys, streets and sidewalks. These four location categories make up 84% of

heroin incident locations, whereas the broad category of "other locations" accounts for the other 16% of heroin incidents.[44] Table D8 suggests that the PDMPs are causing heroin incidents that occur mainly in parking lots and garages (an 84% increase) and on roads (a 71% increase). Anecdotally, heroin sales take place in parking lots and on roadways, often with a simple drive-by transaction or a hand-off exchange between vehicles, and the increase in parking-lot and roadway incidents in response to the PDMP may be a sign of police encountering more heroin transactions in these locations. Also, police may also be encountering more erratic driving as a result of heroin use and may possibly be pulling over greater numbers of under-the-influence offenders in parking lots and on roadways.

Table D9 breaks down the heroin incidents in the most opioid-dense counties by race. It appears the increase in heroin incidents is driven by increases in the rate of heroin incidents among white and black offenders, but the measured increases in heroin incidents split up by race of offender are not individually statistically significant. Table D10 divides heroin incidents into those committed by male offenders and those committed by female offenders, and shows a statistically significant increase in the male heroin incident rate in the most oxycodone-dense counties in response to the PDMP. The point estimate of the increase in female offender heroin incidents is large in magnitude but is not statistically significant. Table D11 classifies heroin incidents by age of offender, and shows that PDMPs affect heroin incidents involving offenders between the ages of 20 and 29, 30 and 39, and 40 and 49. The increases in heroin incidents among 30-39 year-olds and 40-49 year-olds are statistically significant at the 5% level. Overall, white males of a fairly wide range of ages are responding to the PDMP.

Finally, Table D12 breaks down heroin incident rates by both race of offender and across the four most common locations of heroin incidents. This is to examine the effect of the PDMP on offenses by race and location. The PDMP causes an increase in heroin incidents with white offenders occurring in parking lots, within homes, and on roadways. The 0.256 and 0.487 increase in parking lot and roadway incidents add to a combined 0.743 additional heroin incidents by white offenders, which makes up the bulk of the increase of 1.114 additional white-offender incidents, recorded in previous Table D9. Heroin incidents involving black offenders in parking lots and roadways also increase in response to the PDMP, with a combined effect of 0.457 additional heroin incidents, accounting for the bulk of the measured 0.667 additional black-offender incidents in Table D9. In addition, there is a small but statistically significant increase in the rate of heroin incidents involving Hispanic offenders in parking lots.

[44]The "other locations" category includes 54 other types of location categories in the NIBRS and are not listed here.

Table D8: Effect of PDMP on Heroin Incidents in High Oxycodone Density Counties: By Location of Offense

	(1) Disc. Store	(2) Parking Lot	(3) Home	(4) Road	(5) Other
PDMP	-0.00228	0.504*	0.0579	0.724**	0.121
	(0.0102)	(0.255)	(0.0621)	(0.331)	(0.123)
Mandate	0.0330***	0.484***	0.142***	0.562***	0.313***
	(0.00709)	(0.112)	(0.0424)	(0.147)	(0.0827)
Pill Mill Bill	-0.0557***	-0.764**	-0.249**	-0.999**	-0.537***
	(0.0114)	(0.284)	(0.107)	(0.360)	(0.153)
Observations	9588	9588	9588	9588	9588
Fixed Effects	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Controls	X	X	X	X	X
Popln. Weight	X	X	X	X	X
Linear Time Trends					
Mean Rate Per 100,000 Pop	0.0347	0.600	0.1702	1.014	0.278

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The most common locations of crimes in the NIBRS are residences/homes, highways/roads/alleys, department/discount stores, and parking lots/garages, which make up 71% of offenses, and 84% of heroin incidents. The "other" location category makes up the remaining 29% of offenses or 16% of heroin incidents, respectively.

Table D9: Effect of PDMP on Heroin Incidents in High Oxycodone Density Counties: By Race of Offender

	(1) White	(2) Black	(3) Hispanic	(4) Other
PDMP	1.114	0.667	0.156	0.0161
	(0.666)	(0.469)	(0.101)	(0.0115)
Mandate	1.472***	0.496*	0.0412	0.0355**
	(0.278)	(0.240)	(0.0947)	(0.0160)
Pill Mill Bill	-2.432***	-1.080**	-0.109	-0.0484*
	(0.788)	(0.472)	(0.138)	(0.0241)
Observations	9588	9588	9588	9588
Fixed Effects	X	X	X	X
Controls	X	X	X	X
Popln. Weight	X	X	X	X
Linear Time Trends				
Mean Rate Per 100,000 Pop	1.595	0.781	0.379	0.126

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D10: Effect of PDMP on Heroin Incidents in High Oxycodone Density Counties: By Sex of Offender

	(1) Male	(2) Female
PDMP	1.432*	0.508
	(0.753)	(0.293)
Mandate	1.559***	0.444***
	(0.307)	(0.132)
Pill Mill Bill	-2.634**	-1.002**
	(0.907)	(0.334)
Observations	9588	9588
Fixed Effects	X	X
Controls	X	X
Popln. Weight	X	X
Linear Time Trends		
Mean Rate Per 100,000 Pop	2.208	0.574

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D11: Effect of PDMP on Heroin Incidents in High Oxycodone Density Counties: By Age of Offender

	(1) 10-19	(2) 20-29	(3) 30-39	(4) 40-49	(5) 50-59	(6) 60+
PDMP	0.143	1.067	0.479**	0.174**	0.0213	0.0124
	(0.0900)	(0.614)	(0.218)	(0.0735)	(0.0179)	(0.00770)
Mandate	0.0519	1.131***	0.454***	0.202***	0.0808***	0.0222***
	(0.0411)	(0.255)	(0.110)	(0.0510)	(0.0161)	(0.00378)
Pill Mill Bill	-0.212*	-2.141**	-0.854**	-0.219***	-0.0855***	-0.0226**
	(0.115)	(0.720)	(0.293)	(0.0702)	(0.0220)	(0.0101)
Observations	9588	9588	9588	9588	9588	9588
Fixed Effects	X	X	X	X	X	X
Controls	X	X	X	X	X	X
Popln. Weight	X	X	X	X	X	X
Linear Time Trends						
Mean Rate Per 100,000 Pop	0.232	1.252	0.668	0.393	0.130	0.026

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D12: Effect of PDMP on Heroin Incidents by Race and Location Of Offender: Across High Oxycodone Density Counties

	(1) Disc. Store	(2) Parking Lot	(3) Home	(4) Road	(5) Other
PDMP on White	-0.00474	0.256**	0.0591**	0.487***	0.0604
	(0.0101)	(0.0982)	(0.0269)	(0.146)	(0.0599)
PDMP on Black	0.00180	0.230**	0.00467	0.227***	0.0655*
	(0.00368)	(0.0895)	(0.0239)	(0.0846)	(0.0373)
PDMP on Hispanic	0.000133	0.0490*	0.000709	0.0580	0.00482
	(0.00184)	(0.0255)	(0.00437)	(0.0508)	(0.00598)
PDMP on Other/Unrecorded	-0.000961	0.00444	0.000218	0.00387	0.00615
	(0.000923)	(0.00469)	(0.00298)	(0.00238)	(0.00727)
N	9588	9588	9588	9588	9588

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$