Prescription Drug Monitoring Programs on Oxycodone Prescriptions, Heroin Substitution, and Crime Rates

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Justine Mallatt

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Abstract

In response to growing abuse of prescription opioid painkillers, 49 U.S. states have implemented electronic prescription drug monitoring programs which record patients into a state-wide system when a prescription opioid is received. In response to low prescriber utilization of the prescription monitoring databases, 12 states passed legislation that strengthened the prescription monitoring programs by legally requiring prescribers to use the systems. This paper uses a difference-in-differences regression framework and interactive fixed effects factor models to identify the effect of the early prescription drug monitoring programs and subsequent legislation that strengthened the programs on the types and strengths of opioid painkiller prescriptions filled and on drug crime rates. The initial implementation of prescription drug monitoring databases caused a decrease in the amount of oxycodone and strong-dose oxycodone among the Medicaid population. PDMPs cause an increase in the number of crime incidents where an offender is carrying heroin. PDMPs do not affect the number of drug dealers selling heroin, suggesting a demand-side response, which indicates that abusers of high-dose pills substitute to heroin in response to the additional obstacles a PDMP imposes to obtaining prescription opioids. PDMPs have an ambiguous effect on illegally obtained prescription opioids because the databases create opposing market forces. There is no evidence that a mandate requiring that prescribers use the PDMP reduces prescriptions further, and no evidence of the mandates affecting drug crime rates.

1 Introduction

Between 1999 and 2012, sales for opioid painkillers such as oxycodone (OxyContin) and hydrocodone (Vicodin) tripled.[1] Overdoses from prescription opioids and their chemical cousin heroin also quadrupled.[2] In 2014, 18,893 deaths were attributed to prescription opioid painkillers, leading the Center for Disease Control to declare the United States' opioid epidemic "the worst drug crisis in US history."

In response to widespread prescription opioid abuse and overdose, 49 U.S. states have passed legislation implementing prescription drug monitoring programs (PDMPs), which require pharmacists to record a patient's personally identifying information in a state-wide database when that patient receives a Schedule II through V drug.[3] Physicians, pharmacists, law enforcement officials and/or medical licensure boards have access to the databases through an online portal to identify patterns of prescription abuse among documented patients.[4] These programs were intended to curtail abusers' ability to "doctor shop" or "pharmacy shop", terms describing patients who obtain many prescriptions in a short time period from many doctors and pharmacies.

In the time period of interest, although patients are required to be recorded in the PDMP upon receiving controlled substances, PDMPs do not legally require prescribers to query the system for patient drug histories. Many prescribers viewed the programs as burdensome and inconvenient, leading to infrequent usage. Some states require that prescribers create logins for the prescription monitoring databases, and fewer required usage of the systems in specific situations. Prescriber registration and utilization rates of the programs vary state by state, with a median of 35% of painkiller prescribers registering in the system across states.[5] Registration does not ensure utilization, and an assessment of Rhode Island and Florida's PDMPs indicate initial utilization is about 10%.[6] In response to low utilization rates, between 2012 and 2014, 6 states passed laws mandating prescribers to query the PDMP before writing every prescription for controlled substances. [7]

[1]United States Drug Enforcement Agency (DEA) and Centers for Disease Control and Prevention (CDC).

[2]CDC. Vital Signs: Overdoses of Prescription Opioid Pain Relievers – United States, 1999-2008

[3]Drugs receive a Schedule I-V rating based on medical usefulness and possibility of dependence. Illicit drugs like heroin and cocaine are Schedule I with little medical benefit and high potential for abuse. Most opiate painkillers (fentanyl, oxycodone, morphine) are Schedule II; hydrocodone was Schedule III in the time period relevant to this paper.

[4]While pharmacies are required to report patients when a scheduled drug is received, pharmacists and prescribers were not required to look up a patient in the system while prescribing or dispensing opioids until states started requiring it in 2012. As of 2015, 22 out of 49 states introduced mandates requiring providers to check the databases prior to prescribing scheduled drugs.

[5]Kreiner, Nikitin, and Shields (2013)

[6]Poston 2012, Arditi 2014.

[7]Since the end of 2014, 10 more states have passed mandates which require prescribers to check the

Using a difference-in-differences framework, I identify the negative supply shock caused by initial implementation of prescription drug monitoring programs and their subsequent strengthening mandates, examining the changes in quantities, types, and strengths of opioid prescriptions. I then identify the effect of the negative shock to the supply of legal opioids on drug crime rates.

I find that the initial implementation of a PDMP has a negative effect on oxycodone prescriptions through Medicaid, which is driven by a reduction in prescription for high-dose oxycodone drugs. I find no evidence that establishing a PDMP affects crime rates. A mandate that requires prescribers to check the PDMP has no effect on prescription amounts, perhaps due to a very small affected group of patients. However the number of drug crimes increases by 20% in the first quarter of the mandate, driven by a 75% increase in the rate of heroin seizure within police jurisdictions in the affected states. The strengthening mandate also causes a decrease in illegal opiate seizures. The results are consistent with the hypothesis that heavily opioid-dependent users are able to work around the non-mandated PDMPs, perhaps by learning which doctors dispense prescriptions without checking drug histories. However, once prescribers are required to access patient histories before every opioid prescription, some of the heaviest users are no longer able to obtain opiates and switch to heroin.

My paper contributes to existing literature on opioid abuse and PDMPs in two ways. My paper is the first in the literature to view supply-side interventions' effects on substitution behaviors through illegal drug seizures and drug crimes. Secondly, I use a detailed Medicaid prescription dataset that allows me to track how quantities of specific drugs respond to the policies, granting me the ability to disaggregate effects by drug type and strength. Studies conducted at the national level have not disaggregated prescription data by strength. Using the Medicaid data allows me to identify causal effects of the PDMPs on a more disaggregated fraction of the market for opioid prescriptions over geography and time.

2 Factor Model Improvements

My approach is similar to Carey and Buchmueller (2017) in that I also examine not only the initial implementation of a Prescription Drug Monitoring Program, but subsequent legislation that served to strengthen the PDMP by mandating use of the system in specific circumstances. After the implementation of PDMPs, prescriber use was limited. The initial establishment of PDMPs may help identify and deter doctor shoppers, but the patients who

PDMP in specific cases. My outcome data availability restricts me to analysis of 6 policies passed before 2015.

heavily abuse prescription opioids and the drug dealers that rely on prescription opioids for their supply may quickly learn which prescribers check the PDMP and which prescribers dispense opioids uninfluenced by the new systems. Carey and Buchmueller document passage dates of 10 state's PDMP-strengthening mandates, which require prescribers to access PDMPs either with every prescription, initially with new patients or new opioid prescribing regimens, or in the case of prescriber suspicions of patient opioid abuse. It is important to control for the PDMP-strengthening mandates because Carey and Buchmueller find evidence of behavioral responses to the mandates. This paper separates the three policies into different groups, but due to limited post-policy data considers only the strictest strengthening mandates which require prescribers to query patient information for every new prescription. I separate the mandates by type of policy because differing mandates regulate prescriber behavior in distinct ways, presumably causing heterogeneous effects on outcomes. The mandates that require checking every prescription will likely be the most effective at revealing doctor shoppers and limiting the supply of available opioids in the legal and illicit market. Mandates that require that doctors check the PDMP with new patients and new opioid prescribing regimens will not reveal existing doctor shoppers who obtain opioids by visiting the same set of doctors each month. Mandates that require that doctors check the PDMP if they are suspicious of a patient abusing opioids likely don't place much legal liability on doctors and wont have effects on opioid abuse. This paper also examines the effect of supply-side interventions to the opioid market that affect the nation at the same time period but dynamically influence geographies in different ways depending on unobserved geography characteristics. Pacula, Powell, and Taylor (2015) and Albert, Pacula, and Powell (2017) use the nationwide implementation of Medicare Part D in 2006 and nationwide change to the OxyContin formula in 2010 as exogenous shocks to the supply of opioids, and interact the policies with the 65 and over population in a state and the pre-policy OxyContin misuse rates within a state, respectively, to capture differential effects depending on relative effectiveness of the policies. The authors use difference-in-differences approaches with interaction terms that capture heterogeneous intensity-of-treatment of the shocks across geographies. My fixed effects panel factor model approach is more flexible than difference-in-differences and can control for additional meaningful variation in outcome variables that isn't fully captured with difference-in-differences-with-interaction models. The fixed effects panel factor model nests the difference-in-difference interaction models while adding additional flexibility in measurement of time and geography fixed effects, and also controls for unobserved characteristics of geographies by adding meaningful structure to the error term, which is identified and interpreted by the researcher.

3 Background

In 2015, 46,471 Americans died from drug overdoses, making overdose the leading cause of accidental death.[8] Of these overdoses, more than half were caused by prescription painkillers and heroin. Over the past two decades, the United States has become saturated with prescription opioid painkillers such as oxycodone (OxyContin) and hydrocodone (Vicodin), with opioid prescriptions quadrupling between 1999 and 2014. 259 million prescriptions for opioid painkillers were filled in 2012, equivalent to one prescription per adult in the United States. Abuse of habit-forming prescription drugs has risen in turn, and over 10 million Americans reported non-medical use of prescription opioids.[9] Overdoses on prescription opioids also quadrupled in the same time period, with 18,893 people dying from opioid overdose in 2014.[10] The CDC lists prescription opioid abuse as one of the top five public health challenges.

3.1 Opioid Abuse and OxyContin

Up until the 1990s, the opioid-prescribing environment was characterized by "opiophobia," a fear of prescribing narcotic painkillers due to the possibility of dependence.[11] Long-term opioid use was reserved for cancer patients and the terminally ill. Short-term use prescription opioids were largely low-dose formulas combined with over-the-counter painkillers. OxyContin entered the market in 1996 and was aggressively marketed to prescribers as a non-habit-forming treatment for moderate to severe pain because of its "controlled release formulation" of oxycodone. The controlled release mechanism in the form of a wax coating prevented a quick onset and subsequent withdrawal that fosters dependence in users, however original formulations of the drug allowed abusers to gain a fast high by crushing and snorting or injecting the pills. OxyContin quickly became the most prescribed painkiller in the United States, accounting for 30% of the painkiller market and earning $3.1 billion in revenue in 2010. Because of it's extended-release formulation, OxyContin was marketed as a safer opioid to prescribe and came in both typical doses of 10 mg and 20 mg of oxycodone per pill, and also in higher doses of 30, 40, 60, 80 and 160 mg of oxycodone per pill. The aggressive marketing of OxyContin as safe and non-dependence-forming changed the culture of opioid-prescribing. By 2010, 20% of doctor visits where a patient complained of pain

[8] United States Drug Enforcement Agency 2015
[9] National Survey of Drug Use and Health 2014
[10] Centers For Disease Control and Prevention
[11] Atkinson, Schatman, and Fudin (2014)

resulted in an opioid prescription.[12]

Opioid painkiller prescription drugs are similar in chemical structure to opium, morphine and heroin. The opioid class of drugs attach to specific opioid receptors located on nerve cells in the brain, spinal cord, and organs. When opioids attach to the receptors, feelings of pain subside and a relaxed or euphoric feeling may occur depending on the dose and strength of the opioid drug and the person's opioid tolerance. Vicodin (5-10 mg of hydrocodone combined with acetaminophen) and Percocet (5-10 mg of oxycodone combined with acetaminophen) are the most commonly abused opioids according to the National Survey on Drug Use and Health (NSDUH). Although commonly used non-medically, these pills contain relatively small amounts of oxycodone and hydrocodone. A patient may initiate a low-dose regimen of pills, which lose effectiveness over time due to building opioid tolerance, then the patient may require a higher dose. An opioid-tolerant person would need many Vicodin or Percocet pills to obtain the same high or level of pain-relief as one high-dose pill such as OxyContin. Opioid withdrawal symptoms range in severity, and include the return of pain, aches, anxiety, depression, nausea and vomiting, and drug cravings, which lead to high relapse rates.[13] The average person who abuses high-dose OxyContin is likely to be much more opioid-tolerant and opioid-dependent than those who abuse lower-dose prescription opioids.[14]

3.2 Heroin as a Substitute for Prescription Opioids

Heroin and prescription opioids belong to the opioid class of drugs and are substitutes. Widespread availability and abuse of prescription painkillers was followed by increases in heroin use. 75-80% of heroin abusers were initiated into opioid abuse through prescription opioid painkillers prior to adopting heroin, [15] and deaths from heroin overdoses increased by a factor of four between 2001 and 2014, following patterns of prescription opioid overdose.[16] Of the 3.6% of prescription opioid abusers who initiate heroin use, many report transitioning to heroin because of a more intense high, but also due to heroin being more readily accessible and less expensive than prescription opioids.[17]

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[12]Daubresse M, Chang HY, Yu Y, et al. Ambulatory diagnosis and treatment of nonmalignant pain in the United States, 2000-2010. Med Care 2013;51:870–8.

[13]Smyth, Barry, Keenan, and Ducray (2010) "Lapse and relapse following inpatient treatment of opiate dependence. Ir Med Journal June 2010, 103(6):176-179

[14]Abusers of OxyContin in the National Survey of Drug Use and Health are far more likely to report abusing many types of opioids and report more frequent abuse of opioids than the average person who reports abusing a lower dose opioid.

[15]Cicero et al (2014), Jones (2013), Lankenau et al (2012), Muhuri et al (2015)

[16]CDC National Institute on Drug Abuse

[17]Cicero et al. (2014). Prescription opioids have a common street price of $1 per milligram. An 80 milligram pill which would deliver a one-time high for an opioid-tolerant user would cost them $80 when purchased on the black market, whereas heroin sells for $100 a gram, which delivers 10-20 doses. (Inciardi

The type of opioid abuser who is likely to switch to heroin abuses high doses of prescription opioids by snorting or injecting. In the National Survey of Drug Use and Health, respondents who report using OxyContin are much more likely to report also abusing heroin than a respondent who reports abusing weaker opioids like Vicodin and Percocet.

3.3 Supply Side Interventions

In response to rising abuse and overdoses of prescription opioids, lawmakers have established several types of programs aimed at reducing abusers' access to opioids while preserving the availability of these painkillers for those who use them legitimately. Supply-side programs include Medicaid Lock-In Programs, regulation of pain clinics, and reformulations of pills that make them harder to crush. The focus of this paper is on Prescription Drug Monitoring Programs (PDMPs), which are among the most common programs used to attempt to limit opioid availability to abusers.

49 U.S. states have implemented online Prescription Drug Monitoring Program databases between 2001 and 2016. In 1997, Nevada began sending unsolicited reports of individuals believed to be doctor shoppers to the practitioners who had written prescriptions, resulting in a rapid desire for solicited, on-demand reports. In 2001, Nevada developed an online system where prescribers and pharmacists could directly inquire about a patient. Other states followed Nevada's example and by 2015, all states except Missouri had implemented or were currently establishing an electronic online PDMP database.

Previous work on the effectiveness of PDMPs are mixed. PDMPs are often found to reduce the growth rate of oxycodone shipments[18] Several studies have found mixed secondary effects of PDMPs on health and treatment outcomes. Some studies find a reduction in overdoses or poisonings in response to PDMPs [19], whereas other studies find no response in overdoses or emergency department visits [20].

This paper is in the class of several new studies in the economics literature which investigate substitution behavior of opioid abusers following supply-side interventions. Carey and Buchmueller (2017) examine Medicare doctor shoppers behavior in response to PDMPs and PDMP strengthening mandates. PDMPs alone do not significantly affect doctor shopping behavior, but mandates that require that PDMPs be checked under certain circumstances decrease in-state doctor shopping but increase out-of-state doctor shopping, indicating substitution behavior. Alpert, Powell and Pacula(2017) use the abuse-deterrent reformulation of

2009).

[18]Paulozzi and Kilbourne (2011), Reisman, Shenoy et al (2009), Holland and Simione (2006)

[19]Reifler (2012), Simoni-Wastila (2012), Patrick, Fry et al (2016)

[20]Paulozzi and Kilbourne (2011), Maughan, Bachhuber et al (2015), Brady, Lang et al (2014)

OxyContin as an exogenous shock to the supply of prescription opioids and find an increase in heroin-related deaths in states with more OxyContin abuse prior to the reformulation, again adding to evidence that opioid abusers exhibit substituting behavior in response to supply side shocks.

Carey and Buchmueller (2017) differentiate PDMPs by mandates, and find that only strict mandates have effects on doctor shopping behavior. The paper was the first to group states together by details of their PDMP strengthening mandates. Specifically, the authors classify 10 mandate states as having "must access" PDMPs. Within these "must access" PDMP mandates, some states require that prescribers check the databases before every prescription, other states require that prescribers check with new patients and/or new opioid prescribing regimens, some states require doctors to check only if they are suspicious of abuse, and other states' mandates only concern methadone or pain clinics. Since I am under slightly more lax data limitations in that my data covers 2000-2015, this paper separates "must access" mandates into more specific categories. I consider 6 states (Kentucky, Louisiana, New Mexico, New York, Tennessee, and West Virginia) that pass mandates requiring prescribers to query the PDMP upon every prescription for a controlled substance.[21]

3.4 Opioids and Crime

Because prescription opioids are controlled substances, there exists a black market for the pills. In addition, because heroin is a close substitute for prescription opiates, there is reason to believe that legislation that affects the supply of prescription opioids also affects local illicit drug markets. Some doctor-shoppers are drug dealers in that they obtain a large supply of prescription drugs by doctor shopping and can sell the pills for a higher street price.[22] I use drug crimes and drug seizure incidents to proxy for the response of local drug markets to the PDMP.

Implementing a PDMP directly decreases the supply of legal prescription opioids available. In the market for illicit prescription opioids, this creates an increase in demand because illicit opioids are a substitute for legally-obtained prescription opioids that are now harder

[21] I have run additional factor model regressions on mandates requiring prescribers to A.) check the PDMP for new patients and for initiating opioid treatment and B.) access the PDMP in cases where prescribers are suspicious . Only 4 states pass "check initial" mandates (Indiana, Maryland, Nevada, and Vermont) and only 2 states pass "check if suspicious" mandates (Delaware and Ohio) within the timespan of the data I have available, and the analyses I do are imprecise, noisy, not different from zero, and have been excluded from the main paper.

[22] A bottle of 30 pills of 20 mg OxyContin costs about $140 without insurance at major pharmacies. It's common knowledge among the addict community that the street price of OxyContin or opioids is $1 a milligram, meaning that the prescription bottle can be sold for about $600, netting a considerable profit for the seller.

to access. A PDMP also decreases the supply of illicit prescription opioids available because the supply side of the illicit market often obtains the drugs through doctor shopping. The increase in demand and decrease in supply for illicit opioids raises the street price of illicit opioids and has ambiguous effects on quantity traded. A decrease in the supply of legally obtained prescription opioids and an increase in price of illicit prescription opioids will cause an increase in demand for heroin among the heaviest abusers, leading to higher prices in the illicit heroin market and more heroin sales.

4 Data

4.1 Prescription Data: Medicaid State Drug Utilization Data and DEA ARCOS Data

Medicaid tracks the universe of prescriptions the program pays for and compiles the information into reports on the Medicaid website in the Medicaid State Drug Utilization Data. The National Drug Code (NDC) is a unique product identifier that identifies each drug by it's manufacturer, active ingredient, and dosage amount, among other details. The Medicaid data reports the state-by-quarter counts of each NDC. I used the NDC to merge the Medicaid data to detailed information by NDC code from the Food and Drug Administration.[23] For my analysis, I restricted my observations to tablets of opioid painkillers.[24] Different opioids have varying strengths, and I converted all drugs into their morphine milligram equivalent (MME) strength using information by NDC.[25] I identify the effect of the PDMP on all opioids and for oxycodone and hydrocodone, the most commonly abused prescription opioids. The Medicaid data cover 7-15% of the universe of prescription painkillers in the United States.

Because the Medicaid data is at the NDC level, I aggregate morphine equivalent units by both drug type and strength, differentiating morphine units that come in the form of low-dose pills or high-dose pills.[26] I look for heterogeneous effects of the PDMP on drug type by strength and find that, in response to PDMPs, high-dose pills realize greater decreases in

[23]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.

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

[25]For example, 1 milligram of oxycodone converts to 1.5 morphine milligrams, and 1 mg of oxy*morphone* converts to 3 morphine milligrams.

[26]A low-dose pill is a pill with 15 or fewer morphine equivalent milligrams of an opioid. A high-dose pill has greater than 15 morphine equivalent milligrams of opioid. The 15 milligram cutoff was chosen because Vicodin and Percocet have 15 or fewer morphine equivalent milligrams.

prescribing than low-dose formulations.

The Drug Enforcement Agency tracks aggregate shipment amounts of controlled substances through the Automation of Reports and Consolidated Orders System or ARCOS. This data is by state and yearly-quarter level, and by zipcode yearly-quarter level. I use oxycodone and hydrocodone shipments between 2000 and 2014 for my analyses. Table 1 displays Medicaid drug amounts and ARCOS drug amounts in the data.

4.2 NIBRS

The National Incident-Based Reporting System (NIBRS) is an incident-level dataset of crimes committed in 6,251 police districts across 38 states and 1,634 counties. The 2004 NIBRS covered police districts in areas containing 20% of the United States population and accounted for 16% of the complete crime statistics data covered by the FBI. Observations include information about location where the incident occurred, details about the nature of the crime, and demographic characteristics of the offender. For my analysis, I focus on drug crimes involving the purchase, sale or possession of heroin or illegally obtained prescription opiates, and drug seizure amounts. I aggregate the crimes in the NIBRS data into different geography-levels depending on analysis. The NIBRS spans the years 2000-2014, with some new police districts beginning to report in later years. Table 2 displays summary statistics from the NIBRS data.

To identify possible heroin dealers in the NIBRS dataset, I count the individuals per county and month who 1.) are carrying more than 20 grams of heroin, 2.) Are carrying between 10 and 20 grams of heroin and a considerable amount of another drug, or 3.) Are carrying any heroin and were accused of selling any other drug. A probable opiate dealer is someone who 1.) is carrying more than 5 grams or 250 pills of opiates, 2.) Are carrying between 2 and 5 grams or between 100 and 250 pills and are carrying a considerable amount of another drug, or 3.) are carrying opiates and are entered as selling any other drug.

5 Methods

For my main analysis, I utilize both difference-in-differences regression models and a panel data interactive fixed effects factor model from Bai (2009) that improves on difference-in-differences regression models by adding additional structure to the error term. The factor model is important for analyses done at the county level, but at the more aggregated state level, difference-in-differences and the interactive fixed effects factor model perform similarly.

The factor model nests geography fixed effects, time fixed effects, and any existing geography-specific time trends in a way that imposes fewer strong assumptions than a traditional difference-in-differences model does. The interactive fixed effects factor approach allows for common temporal shocks to affect cross sectional units differentially. In using this method, I am able to control for unobserved temporal patterns that are heterogeneous across counties, controlling for additional, previously-unseen confounding qualities. At the county level, difference-in-differences models lead to different results than the factor models. When counties are aggregated to the state level, county characteristics that are related to trends in opioid abuse average out.

Traditional cross-sectional unit fixed effects in difference-in-differences regressions impose a one-dimensional restriction across time. A unit's fixed effect will be equal to its mean difference in level from the aggregate mean across time and cross sectional units adjusted for all other explanatory variables. The factor model approach identifies several meaningful dimensions, or "factors" of variance across states akin to a principle components factor approach. These are referred to as "factor loadings."

Traditional time fixed effects in difference-in-differences regressions impose time-specific effects that are constructed as homogeneous across cross-sectional units. Adding a cross-sectional unit time trend (e.g. State specific linear time trends) allows time trends to differ across geographies, but imposes a strong linear assumption regarding the direction of the time trend. An outcome's time period fixed effect will be equal to its difference in level from the average outcome level across time and cross sectional units adjusted for all other explanatory variables. The factor model identifies common flexible time trends corresponding to each unobserved factor. These time trends affect cross sectional units differently depending on the cross sectional unit's factor loadings. This approach therefore nests both time fixed effects and cross-sectional unit time trends but allows additional dimensions of fit and flexibility.

The difference-in-differences regression for finding PDMP and mandate effects on drug and crime outcomes is:

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

Where $Outcome_{it}$ is prescription opiate density or drug crime rates per 100,000 population in state i in year-quarter pair time t. $PDMP_{it}$ is an indicator that is equal to one if state i has established an electronic Prescription Drug Monitoring Program in quarter t. $Mandate_{it}$ is an indicator equal to one if a state has mandated that prescribers must check the PDMP before writing any prescription for a controlled substance by time period t. X_{it} is a matrix of controls that capture changes within states over time in demographic characteristics and economic characteristics. γ_t and ι_i are time period and state fixed effects, respectively.

Event study graphs are obtained using the underlying equation:

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

$PDMP_{i,t-p}$ is an indicator equal to one if the policy is in started in state i in the time p. The coefficients β_p capture the measured effect of the PDMP 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. $\beta_p \forall p \in \{-5, -4, -3, -2, -1\}$ capture the effect of the policy before it is implemented, and should be zero under the parallel trends assumption of difference-in-differences methodology.

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. Parallel trends holds up well Applied to the case of opioid abuse in the US, there is reason to believe that evolution of abuse-patterns within PDMP and non-PDMP state populations will differ due to local area differences in a population's inherent susceptibility to substance abuse.

Parallel trends also assumes that changes in the policies within states is uncorrelated with the error term. States with the worst opioid abuse problems tended to establish PDMPs early relative to other states, [27] and the only some states with the highest opioid abuse outcomes adopted strict laws mandating physician queries, so the assumption that the error term is uncorrelated with the policy variable is likely to be violated, leading to biased estimates of the policy effects. Because the states that pass the strict mandates are so opiate dense, and have seemingly distinct unobservable characteristics, it is difficult to draw counterfactuals of how the policies affect average states using the difference-in-differences approach. The resulting coefficients from the endogenous equations may be biased away from zero, in that policies may be especially effective in states with many opioid abusers, or may be biased towards zero, in that opioid abusers in the more opioid-dense states may resist or work around the policies somehow, perhaps through prescription drug diversion or substitution to other drugs.

The panel factor model can capture the unobserved confounding sources of variation in the opioid abuse outcome measures. The factors produced can be thought of as omitted variables that explain how opioid abuse develops over time within states or counties. The factor model approach controls for cross-sectional dependence across geographies, and will capture region-specific trends and commonalities in opioid abuse, which is expected to be

[27] For example, heavy-abuse states Kentucky, New Mexico, Nevada, Ohio, Tennessee, Virginia, and West Virginia established electronic PDMPs between 2004 and 2006, whereas South Dakota, Iowa, Minnesota and Nebraska which all have relatively fewer opioid death rates started their PDMPs between 2009 and 2012.

important within Appalachian, Southwest, and Northeastern states. In addition, the factor model allows cross-sectional dependence between distant geographies due to possible unobserved common characteristics that contribute to trends in opioid abuse. For example, the Appalachian, Southwest and Northeastern states may share common trends across regions due to unobserved opioid abuse susceptibility within their respective populations. The factor model approach imposes flexible structure on the error term ϵ_{it} as such:

$$\epsilon_i = \lambda_i' * F_T + u_{it}$$

ϵ_i is a $(T \times 1)$ vector corresponding to state or county i's error term across time. λ_i is a $(r \times 1)$ vector of factor loadings specific to state or county i and F_T is an $(r \times T)$ matrix whose rows contain a normalized factor's path through time. A state or county's ϵ_i can be explain as it's weighted average of a set of meaningful time paths corresponding to factors that capture unobserved state or county characteristics. For example, a factor (normalized in the model to 1) may capture a quality that pertains to unobservable doctor and patient exposure to information about prescription opioids. How exposed a state or county is to the information is captured in the factor loading λi and how state or county opioid abuse responds to the information over time is captured by F_t. A state with a high factor loading on this information factor will place more weight on the corresponding factor time trend than a state with a low factor loading.

6 Results

6.1 PDMPs on Prescriptions

Table 3 shows the state-level difference-in-difference regression results. Columns (1)-(4) are regression results using Medicaid data as the dependent variables, with Column (1) displaying results of the PDMP and the mandate on logged oxycodone morphine equivalent units per Medicaid enrollee. Columns(2) and (3) illustrate the effects of the policies on logged strong-dose Oxycodone and OxyContin density. Column (4) shows the effect of the policies on logged hydrocodone density. Columns (5) and (6) contain regression results from the ARCOS data, and display coefficients from the policies regressed on logged oxycodone and hydrocodone morphine unit shipped to the state per population.

The establishment of a PDMP decreases the amount of oxycodone dispensed to Medicaid patients, and this decrease is driven by an estimated 50.8% decrease in strong-dose oxycodone. Figure 1 shows the results of an event study regression on the effect of the PDMP on oxycodone and strong oxycodone Medicaid drug density. The β_p coefficients of the event study difference-in-differences approach are captured in the graphs. The leads of the policy in each of the graphs are no different from zero, and the effects of the policy begin in the first quarter year after the effective date.

The mandate requiring prescribers to access the PDMP with every controlled substance prescription decreases the OxyContin prescription rate by 70.7%.[28] Figure 2 shows the effects of the mandate on OxyContin prescriptions over time. Unlike the PDMP's immediate effect on oxycodone prescriptions, the mandate doesnt appear to have a strong effect on OxyContin prescriptions until about 7 quarters after passage. Overall, there is not much evidence that adding the additional mandate to a PDMP has an effect on prescriptions. This contradicts results from Carey and Buchmueller (2017) who find that mandates decrease in-state doctor shopping behavior among Medicare enrollees. It may be that doctor shopping is too uncommon to pick up in Medicaid drug quantities, or that I only use states with the strictest mandates, which are a subset of Carey and Buchmueller's "must-access" policy states.

The regression results on ARCOS shipment amounts in Columns (5) and (6) of 3 do not suggest that the policies have strong effects on aggregate shipments of oxycodone or hydrocodone. The ARCOS results are different from the Medicaid data results because the ARCOS cannot be broken down into dosage strengths, and while doctors decrease the rate of prescribing for strong-dose pills in response to the PDMP, there is not evidence that doctors decrease prescriptions for weak-dose oxycodone or prescriptions for oxycodone/acetaminophen combination drugs. In addition, doctors of Medicaid patients may check the PDMPs more for their Medicaid enrollees. Evidence from Blumenschein et al (2012) show that Medicaid enrollees with non-cancer pain prescriptions were likely to have a doctor bring up their prescribing history in a PDMP. Because doctors are more wary of abuse among Medicaid patients, Medicaid drug amounts are more responsive to the PDMP.

6.2 PDMPs on Drug Crimes

Table 4 displays results of difference-in-difference regression models (Columns (1), (2), and (3)) and the interactive fixed effects factor model (Column (4)) on number of incidents where heroin is seized per population in a county-month time period. Coefficient measurements are very sensitive to model specification at the county level. Column (1) is a model with fixed effects only, Column (2) adds county controls, and Column (3) allows for state-specific linear time trends. The coefficient on PDMP switches signs once state trends are added, meaning there are state-differences in heroin seizure trends across states and suggests that there are

[28] I have not yet run the wild cluster bootstrap procedure on this result. I will likely lose statistical significance once I run it.

confounding, uncontrolled-for trends within counties, likely related to unobserved county characteristics. Under the factor model, the passage of a PDMP causes an increase of 0.11 heroin incidents per 100,000 population in a county per month. The average county realizes 1 additional heroin incident per year due to the PDMP. There is not statistically significant evidence that the mandate requiring prescribers to use the PDMP causes a change in the rate of heroin incidents in a county. The increase in heroin incidents due to the PDMP combined with the decrease in strong oxycodone due to the PDMP suggest that the establishment of these databases makes it considerably more difficult to get high-dose prescription opioids, and that opioid dependent patients switch to heroin in response to the PDMP.

Table 5 shows the effect of the PDMP and mandate on incidents where illegal opiates are seized. There is not strong evidence that either policy affects illegal opiate incident rates.[29] Columns (1)-(3) show coefficients from difference-in-differences models with county and time fixed effects, controls, and state-specific linear time trends added to the specification. Column (4) displays results from the factor model. A zero effect of the policies may be due to conflicting forces in the markets for legal and illegal prescription opioids. Decreasing the supply of legal prescriptions make illegal prescriptions more attractive, but the supply side of the black market for prescriptions is also supplied legally, and PDMP will cut off people who doctor-shop to sell to others and people who doctor-shop for self-use. Since the PDMP and mandate affect the supply for legal prescription opioids, and the supply and demand for illegal prescription opioids, the policies' predicted effects on illegal opioid incidents were ambiguous.

In the NIBRS incident-level data, there are incidents where individuals are caught with large amounts of drugs or where the offenders are caught actively selling drugs. I have taken these incidents as drug dealer incidents. Table 6 shows the effect of the PDMP and mandate on the number of probable-heroin-dealer incidents per NIBRS-covered 100,000 population in a county and month. Table 7 shows the results of the PDMP on the number of probable opiate dealers per 100,000 population. Across model specifications, there is little evidence that PDMPs and mandates cause the number of drug dealers to change.

6.3 Discussion

From the difference-in-differences and factor model results on prescription opioid amounts and drug crime, I conclude that the implementation of a prescription drug monitoring program cuts off the supply of strong-dose prescription opioids and increases heroin crime inci-

[29] The difference-in-difference results for the mandate in Columns (1)-(3) have standard errors that have not been adjusted with the wild cluster bootstrap procedure. Inference on these coefficients are likely to be incorrect.

dents.

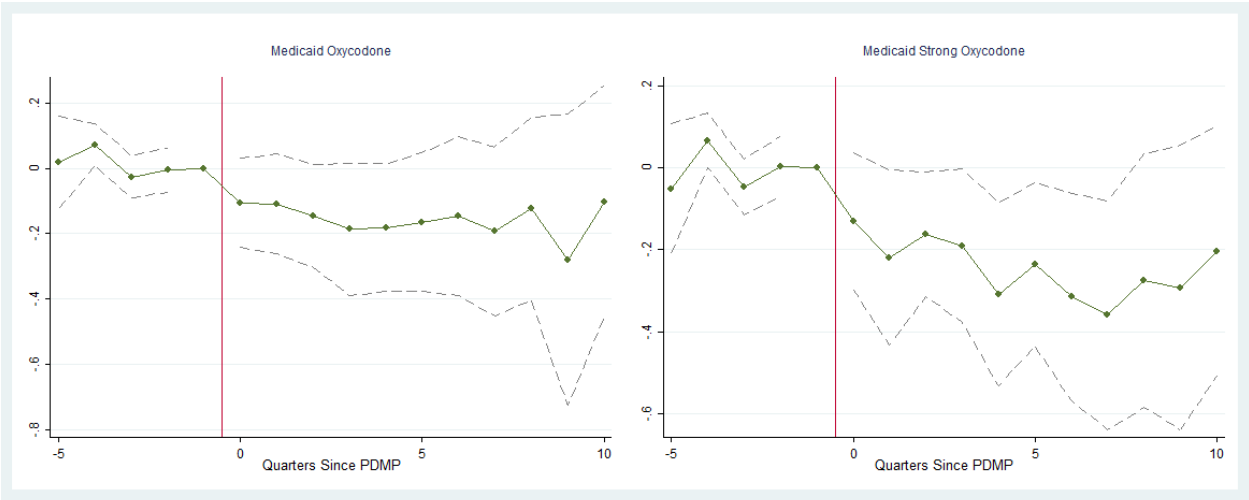

Figure 1: The effect of PDMP implementation on oxycodone and strong-dose oxycodone over time.

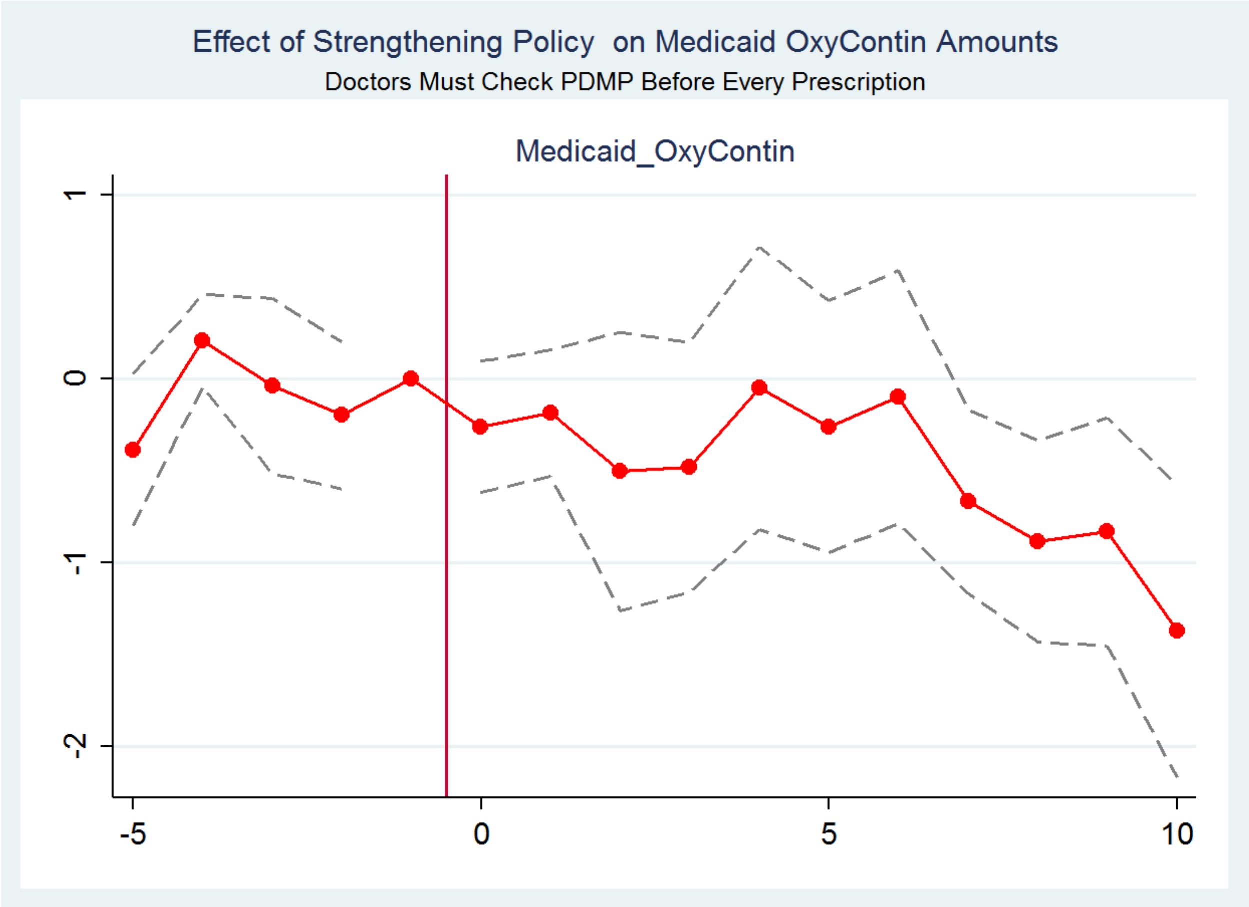

Figure 2: Effect of the mandate on OxyContin amounts filled through Medicaid. Standard errors not yet bootstrapped using the wild cluster bootstrap.

Table 1: Summary Stats 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_WeakDose	–	–	9.083	17.53
Oxycodone_StrongDose	–	–	16.81	34.71
Hydrocodone	149.4	24.68	7.377	11.44
Hydrocodone_WeakDose	–	–	7.377	11.44
Hydrocodone_StrongDose	–	–	0.000338	–
Observations	5100	5100	5100	5100

Panel Data is by state and quarter.

Medicaid data is broken down by drug type and strength. Strong dose pills have more than 15 morphine equivalent milligrams per pill. Hydrocodone in the Medicaid drug data only comes in weak doses.

Table 2: Summary Stats of Crimes, per County/Year/Month

	Obs	Crimes Per 100,000	Std. Error
Heroin Incidents	93,742	0.5912	2.957
Opiate Incidents	93,742	2.7103	8.003
Heroin Dealer	93,742	0.7733	4.908
Opiate Dealer	93,742	0.1797	1.363

Panel Data is by county and month.

The NIBRS covers 717 counties across 25 states from 2004 through 2014.

Table 3: Effect of PMP on Medicaid Amounts- Log(amt/population)

	(1)	(2)	(3)	(4)	(5)	(6)
		Medicaid Data				ARCOS Data
	Oxycodone	Oxy Strong	OxyContin	Hydrocodone	Oxycodone	Hydrocodone
PDMP	-0.380*	-0.508**	-0.209	-0.152	-0.0302	-0.00154
	(0.213)	(0.223)	(0.182)	(0.185)	(0.0335)	(0.0236)
Strict Mandate	-0.0402	-0.213	-0.707*	0.117	-0.115	-0.205*
	(0.671)	(0.603)	(0.389)	(0.547)	(0.0709)	(0.104)
Observations	2716	2682	2718	2588	3081	3081
Fixed Effects	X	X	X	X	X	X
Controls	X	X	X	X	X	X
State Trends	X	X	X	X	X	X

Standard errors in parentheses, clustered by state

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

Panel Data is by state and quarter.

Table 4: PDMP and Mandates on Incidents Where Heroin is Seized Per 100,000 Population

	Diff-In-Diff			Factor Model
	(1)	(2)	(3)	(4)
PDMP	-0.108	-0.0769	0.0877	0.1159**
	(0.103)	(0.101)	(0.0931)	(0.0579)
Strict Mandate	0.516	0.538	0.522	0.3219
	(0.971)	(0.898)	(0.694)	(0.6105)
Observations	93742	89307	89307	89307
FE	X	X	X	X
Controls		X	X	X
State Linear Trends			X	X
Factor Model				X
Bootstrap				X

Table 5: PDMP and Mandates on Incidents Where Illegal Opiates are Seized Per 100,000 Population

	Diff-In-Diff			Factor Model
	(1)	(2)	(3)	(4)
PDMP	0.244	0.146	0.230	0.1814
	(0.279)	(0.180)	(0.158)	(0.128)
Strict Mandate	1.905**	-0.0268	-1.335*	-0.567
	(0.626)	(0.472)	(0.493)	(0.824)
Observations	93742	89307	89307	89307
FE	X	X	X	X
Controls		X	X	X
State Linear Trends			X	X
Factor Model				X
Bootstrap				X

Table 6: PDMP and Mandates on Heroin Drug Dealer Incidents Per 100,000 Population

	Diff-In-Diff			Factor Model
	(1)	(2)	(3)	(4)
PDMP	-0.0686*	-0.0527	0.000685	0.0219
	(0.0312)	(0.0313)	(0.0200)	(0.0221)
Strict Mandate	0.0662	0.0674	0.154	.0444
	(0.228)	(0.213)	(0.200)	(0.220)
Observations	93742	89307	89307	89307
FE	X	X	X	X
Controls		X	X	X
State Linear Trends			X	X
Factor Model				X
Bootstrap				X

Table 7: PDMP and Mandates on Opiate Drug Dealer Incidents Per 100,000 Population

	Diff-In-Diff			Factor Model
	(1)	(2)	(3)	(4)
PDMP	0.0930	0.0505	0.107	0.0224
	(0.118)	(0.0764)	(0.0586)	
Strict Mandate	0.581*	- 0.0463	0.0252	0.0394
	(0.225)	(0.325)	(0.291)	
Observations	93742	89307	89307	89307
FE	X	X	X	X
Controls		X	X	X
State Linear Trends			X	X
Bootstrap				X
Factor Model				X