The Effects of Prescription Drug Monitoring Programs on the Opioid Abuse Epidemic

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Abstract

Opioid abuse is currently the most significant public health problem in the US. Many US states implemented prescription drug monitoring programs (PDMPs) in response. In this paper, I use a new micro-level medical claims database and I exploit state-level and time-series variations in PDMP implementation to shed light on the impacts of these programs. My results show that PDMPs lead to an overall 14% percent reduction in the odds of abuse/addiction. Also, there is evidence of substantial heterogeneity in impacts, with larger impacts for females and minorities. Another finding is that at least 23% of opioid abuse is a result of drug diversion to nonmedical opioid users. PDMPs were not successful in decreasing the rate of abuse for this group and, in fact, there is some evidence that they increased the diversion to heroin. Finally, I show that PDMPs' effectiveness varies by type of insurance and that they are more effective in reducing abuse rates in the general population as compared with Medicare Part D. I use my estimates to analyze the potential effects of modifying PDMPs to include giving insurance providers access to electronic databases, providing educational programs for less-educated people, and expanding their "must access" requirement.

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1 Introduction

Prescription drug abuse has been described by the Centers for Disease Control as an epidemic in the United States. The rate of drug overdose deaths in the United States in 2015 was more than 2.5 times the rate in 1999, with the greatest percentage increase among adults aged 55-64 (from 4.2 per 100,000 in 1999 to 21.8 in 2015) (Hedegaard et al. (2017)). Based on the National Survey of Drug Use and Health, nearly all prescription drugs involved in overdoses are originally prescribed by a physician, rather than, for example, being stolen from pharmacies. Thus, policy makers are increasingly focusing attention on preventing the over-prescription of drugs and their subsequent diversion to people other than the patient.

The main policy response to this prescription drug epidemic is the introduction of Prescription Drug Monitoring Programs (PDMPs), which are in place in all states as of 2017. As part of these programs, statewide electronic databases have been set up to track prescriptions dispensed for controlled substances. Information collected can be used to identify diverted drugs as well as to facilitate the identification of prescription drug-addicted individuals (Finklea et al. (2014)). There are a variety of studies examining the effectiveness of PDMPs as implemented in different states. Haegerich et al. (2014) summarize studies relevant to PDMPs until 2012 and suggest that "PDMP evaluations have detected some positive changes in prescribing patterns, decreased use of multiple providers and pharmacies, and decreased substance abuse treatment admissions and poison center report rates (although findings are mixed)."

In this paper, I evaluate the effects of PDMPs using a new micro-level medical claim dataset, the Clinformatics Data Mart, consisting of 19 million people in 25 states from 2001-2012. First, I perform a descriptive analysis of the trends in substance abuse/addiction during 2001-2012 for different substances including opioids, cocaine, cannabis and amphetamines. I study the correlation between opioid abuse and different substances and possible implications for the characteristics of the abuser population. Second, I use the time and state variation in the implementation of PDMP to perform a difference-in-difference analysis of the effects of PDMPs on abuse/addiction reduction, after controlling for time, state and demographic effects. Further, I study the heterogeneous impact of the program

on different subsamples. I measure how program effectiveness varies by demographic groups and by type of insurance. Third, I combine medical claims with pharmacy claims to identify possible cases of nonmedical opioid abuse, which sheds light on the extent of diversion of opioids from patients to nonmedical abusers. I evaluate the effectiveness of the PDMPs for medical versus nonmedical opioid users by looking at the medical history of each patient. Finally, I study the effectiveness of the program in changing the patterns of prescriptions among providers and the overall probability of taking opioids in the study population. In this section, I perform an analysis similar to Buchmueller and Carey (2017) and Kilby (2016) and compare the results of my study to that of the latest studies conducted on different population groups including Medicare and employer-sponsored individuals .

The Clinformatics Data Mart dataset includes individuals from diverse backgrounds representative of the U.S. population, which enables me to generalize my results to the entire U.S. population. Also, the large sample sizes allow for rich subgroup analysis. Another difference between my study and previous studies is the long time span of data coverage, which makes it possible to test the difference-in-difference assumption of parallel trends and to only include comparison group states that are similar to states that implemented PDMPs. Finally, as individuals' access to prescription drugs also depends to a large extent on their health insurance policies, having detailed information about insurance providers gives me the opportunity to study one of the factors that has not been considered in previous research.

Another novel feature of my analysis is to use the medical claims data as a basis for understanding the problem of drug diversion. Some studies only include people observed to have at least one opioid prescription, but my results show that, among the abuser population, at least 23% did not fill any opioid prescriptions during the year of treatment. My results show that there is not necessarily a close correspondence between dose of medication prescribed and propensity for abuse.

My results show an overall 14% percent reduction in odds of abuse/addiction.The effect is slightly higher for females compare with males, and for blacks compare with whites. The effect is seen most clearly in the low-income population and also in highly educated people. PDMPs decreased the odds of abuse by 17% among low-income families, 12% for

middle income families; there was no significant effect for higher income families. These programs also decreased the odds of abuse by 16% among bachelor degree holders, while no significant effect was evident for people with less than a high school education. PDMPs effectiveness varies significantly by type of insurance, the odds of abuse reduced by 19% for those with HMOs, 11% for those with EPOs and no significant effect for those with PPOs or POS plans. This is intuitive given that insurance policies lead to different patient-provider matches due to in-network and out-of-network provisions. I can see that, although PDMPs provide similar information to all providers, the insurance structure matters for the effectiveness of these programs for each demographic subgroup analyzed. A caveat is that it could be possible that people having an opioid abuse problem would choose insurances that are more generous and more lenient when it comes to getting access to providers that give prescriptions.

Prescription claim histories show that at least 23% of opioid abusers do not have any insurance claims for opioid purchases, which means at least 23% of abuse/addiction cases are the result of opioid diversion. There is no significant effect from PDMPs in abuse/addiction reduction among individuals without opioid prescription claims. Finally, PDMPs have affected other outcomes, including the number of pharmacies and providers visited by patients and quantities of prescribed medications.

2 Background

2.1 Opioid for pain management

Opium has been used for pain management for centuries. The opioid family of drugs continues to be a major part of pain management in medical practice today (Ballantyne and Mao (2003)). Despite its pervasive use, there is little certainty on opioid therapy's risks and benefits.

The first opioid epidemic occurred in the late 19th century, which resulted in the first legal attempts to restrict access to these drugs. In addition to these legal attempts, the introduction of other pain medications limited the use of opioids.

In the late 1980s, however, there was a shift in the discussion of chronic noncancer pain management. Portenoy and Foley (1986) studied 38 cases of long-term opioid therapy, asserting that it was a "humane alternative" to other forms of pain management (e.g. surgery). Similarly, Zenz et al. (1992) observed 100 patients taking opioid therapy lasting 224 days on average and found no cases of addiction. They thus declared opioid therapy as an effective treatment for long-term pain management without addiction being an important concern. Papers with similar conclusions emerged in subsequent medical literature (Fink (2000), Portenoy (1996)). On the ground, the introduction of OxyContin in 1995 shifted the treatment of pain drastically. Purdo Pharma funded more than 20,000 pain-related educational programs to alter physicians' and medical professionals' perceptions of opioid therapy. Although there were no clinical trials to assess the safety of long-term opioid treatment for noncancer patients, the company cited some methodologically flawed papers claiming that the risk of addiction was as low as 1% (Kolodny et al. (2015)). By 1998, "[k]ey organizations that strongly support[ed] the use of opioids to treat chronic pain [...] published consensus statements to guide physicians in prescribing these drugs" (Ballantyne and Mao (2003)).

With these developments, in 1996, the rate of opioid use started to increase. This was followed by an increase in the rate of mortality and morbidity by opioids, but it took policy makers some time to realize that it was not only the nonmedical users who were at risk of overdose. Pain patients who were addicted to opioids were a group that was very likely to

overdose on these drugs (Kolodny et al. (2015)). Furlan et al. (2006), in a meta-analysis of opioid therapy studies, inferred that, despite common belief, "[a]ddiction or opioid abuse in patients with chronic pain cannot be assumed not to exist" because the length of trials are too short for development of addictive behaviors. Martell et al. (2007) investigated the case of patients with chronic back pain and found that, although the effectiveness of these drugs for long-term pain management was unclear, abusive behavior developed in around 25% of the patients. Another review by Højsted and Sjøgren (2007) suggested that the risk of addiction could be as high as 50% in noncancer pain patients. Furthermore, Dunn et al. (2010) investigated the relationship between prescribed doses of opioids and abusive behavior and concluded that "[p]atients receiving higher doses of prescribed opioids are at increased risk of opioid overdose, underscoring the need for close supervision of these patients."

In response to this growing public health risk, policy makers first targeted illegal access, but as inappropriate use among patients became more clear by 2005, different policies focusing on this segment emerged. The Prescription Drug Monitoring Programs, which are described in the following section, are the most important of these policies.

2.2 Prescription Drug Monitoring Programs

Prescription Drug Monitoring Programs (PDMPs) are state-administered databases that contain information on the prescribing and dispensing of controlled substances. Information contained in the PDMPs may be used by doctors and pharmacists to identify patients who may be doctor shopping (seeing multiple doctors to obtain prescriptions), need substance abuse treatment, or are at risk for overdose. In accordance with state laws, PDMP information may also be used by state regulatory and law enforcement officials to pursue cases involving inappropriate prescribing or dispensing, so-called "pill mills," or other sources of diversion.

The first PDMP was established in California in 1939, and as the need to collect data on prescription drugs for law enforcement and monitoring purposes grew, 8 more states established this program by 1989. In this period, which is called the "Paper Era" of the PDMPs, the information was mainly used by law enforcement agencies to curtail diversion.

By 1990, the "Electronic Era" of the PDMPs began, which made the sharing of data easier between providers, pharmacists and drug agencies. In the next decade, the steady rise in the abuse and diversion of controlled substances further increased the importance of PDMPs, and eventually there was a drive to align and consolidate the programs in different states, which so far differed vastly in regulations and implementation. Thus started the "Federal Era" of the PDMPs in 2002, when the the National Alliance for Model State Drug Laws (NAMSDL) drafted a model program outlining common goals that should be shared among existing and new PDMPs (Blumenschein et al. (2010)). As a result, PDMPs that were enacted in states after 2003 were very similar, and their enactment can be viewed as a natural experiment in contrast to the early PDMPs that were started in states with high abuse rates.

The impact of PDMPs has been studied in three main areas: effects on provider behavior, patient behavior and health outcomes. PDMPs resulted in a decrease in the number of prescriptions for schedule II narcotics such as oxycodone but resulted in an increase in prescriptions for schedule III pain killers such as hydrocodone, which are easier to prescribe. Overal, however these programs decreased inappropriate prescription behaviors. For patients, PDMPs decreased patients' visits to multiple pharmacies and discouraged doctor shopping. A survey of Ohio, California and Kentucky prescribers shows that access to new information on patient history through PDMPs has changed their prescription behavior. Results from Wyoming, Nevada, Massachusetts and Maine show that mandatory access to the PDMPs has decreased both doctor shopping and prescribed doses by doctors (of Excellence (2012), Haegerich et al. (2014)).[1]

The effects of PDMPs on health outcomes are less clear. Simeone and Holland (2006), found a significant reduction in substance abuse treatment admission, and Reifler et al. (2012), show a significant decline in the rate of growth of abuse. On the other hand, while Reifler et al. (2012), and Reisman et al. (2009) found a decline in abuse-related admissions, it was statistically insignificant, and Paulozzi et al. (2011) found no significant change in

[1]Haegerich et al. (2014) summarize studies relevant to PDMPs including Pletcher et al. (2008), Curtis et al. (2006), Simoni-Wastila and Qian (2012), Wastila and Bishop (1996), Reisman et al. (2009), Simeone and Holland (2006), Dormuth et al. (2012), Ross-Degnan et al. (2004), Pearson et al. (2006), Dormuth et al. (2012)

drug overdose mortality (Haegerich et al. (2014)). Meara et al. (2016) studied disabled Medicare beneficiaries as a high-risk group and concluded that "[a]doption of controlled-substance laws was not associated with reductions in potentially hazardous use of opioids or overdose."

Some studies suggest the primary factor behind insignificant health benefits from PDMPs is low or infrequent access of the database by prescribers. A 2015 study of primary care prescribers found that, while a majority reported having obtained data from their PDMP at some point in time, where participation in the PDMP was voluntary prescribers checked the patient history only 14% of the time before prescribing an opioid (Rutkow, L. et al. (2015), of Excellence (2014)). In line with this finding, most recent studies focusing on the attributes of the program show a higher degree of success. Buchmueller and Carey (2017) provide evidence that "must access" PDMPs significantly reduce measures of misuse in Medicare Part D. In contrast, PDMPs without such provisions have no effect.

A far as I know, the effectiveness of PDMPs for people with different individual characteristics is not studied in the literature. Although it is known that, the risk hazard of opioid abuse is different among different population groups. For example, Paulozzi (2012) summarizes the literature on prescription drug use through 2011 and concludes that demographic characteristics most likely associated with abuse include being male, middle aged, white, low income and suffering from mental health issues. African Americans and Hispanics are less likely to be prescribed any drugs (Gu et al. (2010)), including controlled prescription drugs (Centers for Disease Control and Prevention (2006)), and are less likely to report nonmedical use of prescription pain relievers (Substance Abuse and Mental Health Services Administration (2011a)).

3 Data

My primary dataset is the medical and prescription drug claims dataset, Clinformatics Data Mart (CDM) for years 2001-2012. CDM contains administrative health claims for members of a large national managed-care company affiliated with OptumInsight. It includes individuals with both medical and prescription drug coverage, having data for approximately 15 million people annually, for a total of more than 40 unique million individuals over a 10-year period. CDM largely consists of commercial health plan data but also contains historic claims for Managed Medicaid and Medicare.[2] The population is geographically diverse, spanning all 50 states. CDM includes demographic and geographic information relating to gender, age, and state of residence, in addition to medical and pharmacy claims.

I include the states that implemented the PDMP for the first time between 2003 and 2012.[3] Prescription drug monitoring programs that were implemented during this period belong to the "Federal Era" of the PDMP and have generally similar characteristics.As the implementation of the policies can happen anytime during a year, I will consider PDMPs being active in a year if the user access date began before July of that year.

The PDMP Training and Technical Assistance Center (TTAC) and The National Alliance for Model State Drug Laws (NAMSDL) are the main sources providing information on the date of operation for PDMP programs, with some disparities for a couple of states. NAMSDL reflects the date that prescribers and/or dispensers were allowed to have access to PDMP information, whether electronic or hard copy, while TTAC's category reflects the date that the programs began receiving and storing data electronically.[4] Table 1 reports the implementation date provided by NAMSDL.[5] In addition, I use the Prescription Drug Abuse Policy System, which provides detailed data of variation in state laws regarding implementation of PDMPs up to 2016 using the relevant legislative documentations to examine the similarities and disparities among the states in my study.[6] States that I include in my

[2]Medicare Choice after 2006 and Medicaid after 2011 are not included, so I remove these individuals from my analysis.

[3]No state started its program at 2001 or 2002.

[4]This information is provided by Heather Gray, the legislative director of National Alliance for Model State Drug Laws.

[5]Accessed on June 2015: http://www.pdmpassist.org/pdf/PPTs/LE2012/1_Giglio_HistoryofPDMPs.pdf

[6]Data accessed on Oct 2016 at www.pdaps.org

analysis provide access to prescribers, dispensers and the regulatory board. Dispensers have to report data to PDMPs; however, access to PDMPs before prescribing is not mandatory, and PDMPs are not allowed to share the data with private insurers. PDMPs differ in their permission or requirement to identify suspicious activity and take any action, such as reporting suspicious activities to law enforcement or provider/dispenser. By restricting the data to these 25 states, and people 11 to 65 years of age, my final sample includes around 6 million people annually for approximately 19 million unique individuals.

3.1 Trends in prescription drug abuse/dependence, co-occurrence with other substance use disorders

There have been some controversies about the underlying factors for opioid abuse or dependence, as these drugs differ from other street drugs in that they are the only ones that can be accessed for legitimate medical reasons but lead to dependence. At first, policy makers assumed that abuse or dependence on these products occurs only among people who do not have a medical prescription for opioids; however, they later found that there is such a thing as accidental dependence. The possibility of opioid abuse/dependence among medical users shifted the focus of drug control from solely the distribution level to the patient level as well.

Incidence of abuse/dependence among pain patients suggests that long-term opioid therapy may lead to dependence and abuse. At the same time, nonmedical abuse is also prevalent. Surveys show that the main source for nonmedical use of opioids is prescriptions written for friends or family members, which suggest over-prescription of these drugs. Understanding the inherent differences between these two groups of people, medical and nonmedical users, is important for effective policy making.

Surveys on nonmedical users of opioids suggest that these people are also more likely to abuse other drugs (McCabe et al. (2008)); therefore, studying the demographics of abusers with multiple substance problems, in combination with their medical history, should provide a picture of these types of abusers and how they differ from patients on opioid therapy who ended up as abusers. At first, I look at the trend of abuse or dependence for different

substances. I identify substance abuse, addiction or poisoning by applying the ICD-9[7] codes listed in Table 2 to the five provided diagnoses codes in each medical record. Descriptions associated with each ICD-9 code are provided in the documentation for the CDM data. [8]Similar diagnoses in a given day, or as part of one insurance claim, counts as one visit. Figure 1 provides the number of visits during 2001-2012 for each substance. A visit to an inpatient or outpatient facility can be the result of abuse of multiple drugs, each one recorded with different diagnosis code. I count the substance reported first as the primary substance.

The total cases of substance abuse/dependence more than doubled during these 10 years, but the growth has been fastest for the opioid drug family. The total number of admissions in this group more than quadrupled. Further, the rates and trends in admissions by each cause, especially for alcohol and opioids, are similar to those reported by SAMHSA (2014*b*), which confirms that this dataset closely represents the United States population. Table 3 shows that more than 99% of opioids reported in cases of abuse/dependence are prescription opioids. The share of these drugs is constantly increasing, while percentage of heroin-related cases decreased from 0.53% to 0.36%, and methadone-related cases decreased from 0.29% to 0.09%.[9]

The studies based on the treatment admission data without specific individual identifiers may provide biased information about the characteristics of the population under study. I estimate the average number of visits for each type of drug abuse/dependence by dividing the total number of visits in each category by the total number of unique individuals in each one. Table 4 shows these multiple visits during a year are common for all type of substances. A person with an opioid abuse or dependence problem on average visits inpatient or outpatient facilities seven times a year. So instead of studying the pop-

[7]International Classification of Diseases, Ninth Revision.

[8]I use ICD-9 codes provided by the Centers for Disease Control and Prevention to identify poisoning cases: https://www.cdc.gov/drugoverdose/pdf/pdo_guide_to_icd9cm_and_icd10_codesa.pdf; I use the description provided for each code to identify the cases of addiction for each substance. My list is similar to other studies with slight differences; for example, Meara et al. (2016) use similar codes to identify nonfatal opioid-related abuse cases, but they also include E950.0, which is associated with suicide. In addiction to that, my list includes dependence to opioid cases.

[9]Cases of methadone abuse/dependence are identified with ICD-9 codes different from other prescription opioids as reported in Table 2. For the rest of the analysis, I consider methadone as part of prescription opioid cases.

ulation characteristics of admitted people, it is more informative to investigate the effect of policies to the number of unique individuals with a treatment record for abuse or addiction.[10] To study the population characteristics of the abusers, I aggregated the data annually, indicating if each individual had cases of abuse/dependence for alcohol, opioids, cocaine, amphetamines or cannabis. Figure 2 shows the number of people who visited medical providers for any substance misuse during 2001-2012. The trends are similar to those reported by SAMHSA (2014*a*), which comes from the National Survey on Drug Use and Health. In 2001, the number of people with cannabis abuse problems was around 20% higher than opioid abusers/addicts, but opioid cases have grown much faster, and by 2012, there were twice as many cases of opioid abuse. Fortunately, the total number of individuals with cocaine abuse problem declined, and the number has stayed almost constant since 2005 for those with cannabis and amphetamine abuse problems. Table 5 shows that there is a high correlation between the abuse of different types of substances with the highest being 0.35 for the correlation between opioid and other medications abuse. The correlation between abuse of opioids and other substances including cocaine, cannabis and amphetamines is 0.18, 0.14 and 0.10, respectively. For the rest of the data summary, I focus on individuals with a prescription opioid abuse/dependence history.

Table 6 shows that people who visit medical providers for only opioid misuse are on average 3.5 years older than people who get admitted for a combination of drugs, including opioids. this provides some suggestive evidence that the older population uses opioids for medical reasons rather than for recreational purposes. Figure 3 shows the percentage of the people abusing opioids in each age group during 2001-2012. The probability of abuse is almost the same, 0.1%, among those 18-54 years of age in 2001, but it is increasing with a different rate among different age groups. The probability goes to 0.79% for those 18-23 years of age (620% rate of growth) and 0.55% for those 24-33 years of age (399% rate of growth). The rate of growth is drastic among the elderly as well, it goes from 0.06% to 0.26% (376% increase).

Providers prescribe opioids differently for different demographics based on age, gender

[10] SAMHSA (2014*b*) and other studies using TED dataset used these type of analysis because of lack of identifiers for individuals.

and income or race/ethnicity. Pletcher et al. (2008) argue that white people are more likely to get opioids for pain-related admissions to emergency rooms in comparison with other races, and even the "national quality improvement initiatives" of the 1990s did not reduce this gap. PDMPs aim to provide information about the medical history of patients to improve the practice of prescribing controlled drugs, but it is not clear how these programs affect the already existing biases. I will investigate this using regression analysis in the next section.

4 Econometric Analysis

4.1 Effect of PDMPs on prescription opioid and heroin abuse/dependence

I first consider the effect of PDMP implementation on the abuse/dependence of prescription opioids and heroin in the whole population. I estimate the following regression models:

$$y_{it} = \alpha + \gamma_i + \lambda_t + \tau(pdmp_{st}) + \epsilon_{ist} \tag{1}$$

$$y_{it} = \alpha + \gamma_i + \lambda_t + \sum_{l=-4}^{l=+4} \tau_l(pdmp_{s,t+l}) + \epsilon_{ist} \tag{2}$$

Here, y_{it} is an indicator for patient i abusing either heroin or prescription opioids in year t, γ_i is the individual fixed effect, λ_t is the time fixed effect, $pdmp_{st}$ is an indicator for active PDMP in state s during year t and $pdmp_{s,t+l}$ is an indicator for active PDMP in year $t + l$. The event study analysis in the second equation is necessary to test the validity of the parallel trend assumption in difference-in-difference analysis, it confirms that the implementation of PDMPs for the set of states included in my analysis qualifies as a natural experiment. Figure 4 shows the estimation results of equation 2. It is clear that after controlling for individual and year fixed effects, there is no significant trend in the abuse of prescription opioids or heroin before implementation of PDMPs among states included in my data. Figure 4 shows that the implementation of PDMPs reduced the probability of prescription drug abuse/dependence but gradually increased the probability of heroin abuse/dependence. The increase becomes significant two years after the program.

4.2 Effect of PDMPs on prescription opioid abuse/dependence in sub-samples

In this section, I study the individual characteristics that determine the effectiveness of the programs in reducing prescription opioid abuse/dependence for each sub-sample. I first estimate the model including individual characteristics and the interaction between characteristics and PDMP implementation instead of individual fixed effects:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + X_{it}\beta_0 + pdmp \times X_{it}\beta_1 + \epsilon_{it}$$

In which X_{it} is a vector including age, gender, race, income, education and type of insurance. I use the logistic regression in order to accommodate the smaller sample size in some of the subgroups. In Table 7, I report the results of this estimation in comparison to the model without individual controls and the model without the interaction of individual characteristics and PDMP implementation. The interaction terms, although not reported here, are significant and different among different demographic groups. To investigate this heterogeneity more closely, I divide people by their income, race, gender, education and type of insurance. Then I estimate a similar logistic regression for each group:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + X_{it}\beta_0 + \epsilon_{it}$$

X_{it} includes all individual characteristics not used in categorizing people in sub-samples. Although the type of insurance seems to be an endogenous variable, it is unlikely that it will be affected by the event of abuse or addiction. In Table 9, I show that the effectiveness of the program decreases by family income even after controlling for education level. The odds of opioid abuse decreases by around 18% for individuals from low-income families (less than \$40,000), 10 to 13% for individuals from middle-income families (\$40,000-\$75,000), while having no significant effect for people from higher-income families. Table 10 shows that the effectiveness increases by individuals' education level; people with a higher education are less likely to abuse prescription opioids after implementation of PDMPs. The reduction in the odds ratio is the highest for those with bachelor degrees (17%). PDMPs subsequently

decrease the odds ratio of those with bachelor degree by 16% and those with high-school diploma with 11%. It is important to notice that these effects are estimated after controlling for family income level, age and gender, which suggest one mechanism for effectiveness of these programs is informing individuals about the risks of opioid use.

Table 11 reports the results by the type of insurance. It suggests that HMO insurance holders benefit the most from PDMPs, followed by those with EPOs. PDMPs resulted in a 20% reduction of the odds of abuse for those with HMOs, a 12% reduction for those with EPOs and no significant effect for people with PPOs or POSs. This is intuitive given that insurance policies lead to different patient-provider matches due to in-network and out-of-network provisions. I can see that, although PDMPs provide similar information to all providers, the insurance structure matters for the effectiveness of PDMPs for each demographic subgroup analyzed. A caveat is that it could be possible that people who have an opioid abuse problem would choose insurances that are more generous and more lenient when it comes to getting access to providers that give prescriptions.

4.3 Relationship between the abuse/dependence and prescription

The next step in analyzing the abuse/dependence of prescription opioids is to understand the relationship between abuse and prescriptions for opioids. To investigate the relationship between abuse and prescription, I assign an indicator $rx = 1$ to each individual-year if a person has an opioid prescription filled during that year. I identify narcotic in prescription claims data by using universal standard classification codes (usc-id) provided by the CDM for each drug. '022**' is the usc-id code for any form of narcotics, tablet, capsule, patch, etc. at any strength, including less controlled and more easily prescribed narcotics such as acetaminophen-codeine. There are hundreds of different opioids in the data with highest frequency being for Oxycodone, hydrocodone, codeine and propoxyphene. To have a valid measure to compare different prescriptions over time, I use the morphine equivalent of each prescription by multiplying the quantity of the drug being prescribed by the milligram morphine equivalent (mme) factor for each drug and then aggregating the data for each individual for each year to find the total mme of prescribed medication. In addition, I find the total days of supply, the number of distinct pharmacies and the providers that each

patient visited to get prescriptions for opioids which I will use in the next section. Then, I combine medical history with prescription claims data to investigate the effects of being prescribed any type of narcotics in opioid abuse/dependence.

Information from Table 12 shows that 69.3% of the people did not fill any prescription for a narcotic during their coverage period in my data. Among the 30.7% of the people who have been prescribed opioids, only 0.92% have records of abuse/addiction. On the other hand, among the narcotic abusers/addicts, we can see that 22.98% never filled a prescription. This table shows that the problem of diversion of drugs is serious. It is important to notice that this table overestimates the number of prescription for narcotics. I include all the prescriptions filled for any type of narcotics at any dose and quantity. The morphine content of some prescriptions is very small, which makes it impossible to cause any sort of abuse or addiction. In Table 5, I look at the population that ever been prescribed any narcotics and the population of abusers separately throughout the years from 2001 to 2012. In the sample of people who have abused opioids in each year, around 37% had not been prescribed any opioids in 2001, and this number increased throughout the years, which means that abuse of narcotics without prescriptions prevails over these years. These numbers are just a rough estimate since patients could save prescriptions in a given year and abuse them in the future. But as we saw in Table 12, even after pooling the data over the years, the number of abusers/addicts with no prescriptions is at least as high as 23%, so the actual number may be somewhere in between. In the sub-sample of people who received opioid medication, 0.49% abused opioids in 2001, and this number constantly increased and reached 1.25% in 2012. As we saw in Table 12 even if we include all the prescription claims throughout the coverage, only 1% of total individuals filling a prescription ended up abusing it themselves.

Although different surveys show that friends and family are the main sources of opioids among nonmedical users (McCabe et al. (2007)), it is not possible to find the source of these drugs in my data. It is only possible to study the demographic of this population to provide a more accurate guideline for providers. In Figure 6, it is clear that the distribution of the age of nonmedical abusers is tilted to the left, suggesting that the younger population uses these drugs for recreational purposes, especially people younger than 24 years of age. On

the other hand, among those 54-64 years of age, it is twice as likely for abusers to be getting the drugs through prescription rather than other sources. I similarly look at the patterns by other demographics. Although not as clear as in the case of age, it seems that whites and females who abuse opioids are more likely to get them through prescriptions. I estimate the effectiveness of PDMPs in preventing diversion by estimating a regression model similar to that of the previous section for two groups of people- those who filled any prescription for opioids and those who have not:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + X_{it}\beta_0 + \epsilon_{it}$$

X_{it} includes total mme and days of supply of medication for people who filled any prescription for opioids. Table 13 shows that, after controlling for mme and days of supply, implementation of PDMPs reduced the odds of opioid abuse by 10% among patients, but they did not have any significant effect on the abuse of opioids among nonmedical users. One of the goals of PDMPs was to reduce the diversion of opioids by restricting the access to these drugs among patients, but my results suggest that these programs did not provide any benefit of this sort.

4.4 Patterns of opioid prescription

One of the more studied aspects of PDMPs is the study of the effect they have in the patterns of prescriptions. I perform a series of analyses similar to Kilby (2016) and Buchmueller and Carey (2017). I estimate the model:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + \epsilon_{it}$$

In which y_{it} measures total mme for each patient i at year t. The results in Table 16 show a reduction in prescribed opioids similar to the finding in Kilby (2016) from analyzing Automated Reports and Consolidated Orders System (ARCOS) data. But non of the specifications resulted in a significant estimation.

I follow the Buchmueller and Carey (2017) in constructing some proxy measures of

misuse consisting of quantity-based outcomes and shopping outcomes. The first measure is the share of enrollees that took any opioids at all. The other quantity-based outcomes are intended to capture patterns that are indicative of misuse or dangerous for individuals' health. It includes an indicator for higher than 391 days of supply in year (more than thirteen thirty-day prescription), having a daily average of opioid use higher than 120 milligram morphine equivalent (mme). The shopping outcomes include indicator for patients who visited more than 10 prescribers in a year to get prescription for opioids and more than 10 pharmacies to fill their prescriptions for opioids. I report the summary statistics of these variables in Table 14. To evaluate the PDMP effect on these variables, I use the aggregate level difference in difference analysis:

$$y_{st} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + \epsilon_{it}$$

Here, y_{st} in the frequency of outcome in each state year divided by the total number of population with at least one prescription for opioid. γ_s and λ_t represent state and year fixed effects and standard errors clustered at state level. I weighted each observation with value of denominator. I report the results of these estimations in Table 17. These results can be compared with the results of Buchmueller and Carey (2017) for the states without the "must access" PDMP requirement. Buchmueller and Carey (2017) do not find any significant effect for similar variables and conclude that without the "must access" specification PDMPs are not effective. My estimation shows that PDMPs effectively reduce the cases of +391 days of supply among prescription holders. The rate of visiting more than 10 pharmacies decreased by 0.034%. Similar to the individual level analysis in previous section, the rate of opioid abuse significantly decreases among people with prescriptions. The discrepancy among the results of the two studies are likely to be the results of the difference between sthe ubsample population in each study. Buchmueller and Carey (2017) study the Medicare part D beneficiaries while my analysis represents the whole population, which means that PDMPs are more effective in reducing opioid misuse among the general population in comparison toreducing opioid misuse among Medicare part D beneficiaries.

4.5 Limitation

There are limitations that arise from the use of the ICD-9 codes in identifying abusers, similar are mentioned in other studies that use this method (White et al. (2009)). This way of identification is likely to underestimate the number of cases for two reasons. Individuals experiencing nonfatal overdoses also might be less likely to seek care because they expect disapproval or legal consequences (Paulozzi (2012)). Also, if patients don't use insurance for payment of medical treatment, I won't be able to observe them in this dataset.

5 Conclusion

Despite the strong emphasis of the role of Prescription Drug Monitoring Programs on the war on prescription drug abuse, there has not been much conclusive evidence in the literature that these programs actually reduce the abuse of these drugs. In this study, I analyze opioid addiction in addition to opioid poisoning to measure the health benefits of the PDMPs. Using a nationally representative dataset, including 25 states from 2001-2012, I show that PDMPs have been effective in reducing the probability of abuse/addiction of opioids. The effect is heterogeneous among different groups based on their income, education and ethnicity, but more importantly, the effect is heterogeneous for people holding different insurance policies. This suggests that some practices among HMO insurance providers, including a close network of providers and referral requirements for visits to specialists, may prove to be valuable when it comes to fighting the opioid abuse epidemic.

Table 1: Year of PDMP implementation

State	Year	State	Year
Alabama	2008	Massachusetts	2011
Alaska	2012	Minnesota	2010
Arizona	2009	Mississippi	2006
Arkansas	2013	New Jersey	2012
Colorado	2008	New Mexico	2006
Connecticut	2009	North Carolina	2008
Delaware	2013	North Dakota	2007
Florida	2012	Ohio	2007
Georgia	2013	Oregon	2012
Indiana	2007	South Carolina	2008
Iowa	2009	South Dakota	2012
Kansas	2011	Vermont	2009
Louisiana	2009	Washington	2012
Maine	2005	Wyoming	2004

Notes: The implementation years are user access dates reported by NAMSDL. PDMPs are considered active in a year if providers have access to the PDMP before July of the implementation year.

Table 2: ICD-9 codes of abuse or addiction

ICD-9 code	Description
303	alcohol dependence syndrome
3050	nondependent alcohol abuse
980	toxic effect of alcohol
3040	opioid type dependence
3055	nondependent opioid abuse
9650	poisoning opiates & related narcotics
E850	accidental poisoning-analgesic
96501	poisoning by heroin
E8500	accidental poisoning by heroin
96500	poisoning by opium, unspecified
E8502	accidental poisoning other opiates& related narcotics
96509	poison opiates& related narcotics oth
3047	comb opioid rx w/any other rx depend
96502	poisoning by methadone
E8501	accidental poisoning by methadone
3042	cocaine dependence
3056	nondependent cocaine abuse
3043	cannabis dependence
3052	nondependent cannabis abuse
3044	amphetamines & other psychostimulant depend
3057	nondependent amphetamine
3059	other mixed/unspecified nondependence drug abs
E8589	accidental poisoning unspec drug
97***	poisoning by other prescription drugs
98***	toxic effects of other prescription drugs

Notes: The codes for opioid and other drugs abuse/dependence. For the caes of opioid abuse includs reported codes used by recent papers including Meara et al. (2016) and Buchmueller and Carey (2017).

Table 3: Number of visits for abuse/dependence by opioid categories

	Year (frequency)											
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Heroin	284	397	398	414	320	340	294	427	501	456	566	812
Methadone	153	276	254	462	418	374	385	536	389	205	187	203
Rx opioid	52954	58022	66346	62011	75412	77409	96589	128188	168355	163431	167587	225410
Total	53391	58695	66998	62887	76150	78123	97268	129151	169245	164092	168340	226425
	Year (percentage)											
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Heroin	0.53	0.68	0.59	0.66	0.42	0.44	0.3	0.33	0.3	0.28	0.34	0.36
Methadone	0.29	0.47	0.38	0.73	0.55	0.48	0.4	0.42	0.23	0.12	0.11	0.09
Rx opioid	99.18	98.85	99.03	98.61	99.03	99.09	99.3	99.25	99.47	99.6	99.55	99.55
Total	100	100	100	100	100	100	100	100	100	100	100	100

Notes: Cases of methadone abuse/dependence are identified with ICD-9 codes different from other prescription opioids as reported in Table 2. For the rest of the analysis, I consider Methadone as part of prescription opioid cases.

Table 4: Average number of visits per person to inpatient/outpatient facilities for each substance

Substance	Average number of visits
Alcohol	4.2
Opioids	6.6
Cocaine	3.9
Cannabis	3.9
Amphetamines	3.2

Notes: In this table, I report the average number of visits for each substance in all 50 states during 2001-2012.

Table 5: Correlation between admission for different type of substances

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
(1) Alcohol	1					
(2) Opioids	0.158	1				
(3) Cocaine	0.184	0.181	1			
(4) Cannabis	0.205	0.140	0.194	1		
(5) Amphetamines	0.103	0.105	0.118	0.160	1	
(6) Other meds	0.185	0.354	0.182	0.170	0.122	1

Notes: Pairwise correlations for abuse/dependence among different substances incidents. All the numbers are significant in 0.001 level.

Table 6: Age difference among different types of abusers

	Mean age
Only opioids	38.519
	(1.896)
Opioid with other substances	35.057
	(2.402)
Diff(1-2)	3.462***
	(2.146)

Note: This table reports the mean age of the individuals that only abuse opioids, and compares them with people who abuse opioids in combination to other substances.

Table 7: Effect of PDMPs on probability of abuse/addiction

	(1)	(2)	(3)
PDMP	-0.186^{***}	-0.154^{***}	-0.085^{**}
	(0.010)	(0.010)	(0.043)
Controls:			
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Ind. Controls	No	Yes	Yes
PDMP × Ind. Controls	No	No	Yes
R−Square	0.019	0.040	0.041
Observations	62,708,948	56,719,688	56,719,688

Notes: Coefficients of logit regression for probability of an individual diagnosed with abuse/addiction of prescription opioid. Individual controls include age, gender, education, income and type of insurance. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 8: Effect of PDMPs on probability of abuse by gender, race category

	Black		*White*	
	Female	*Male*	*Female*	*Male*
PDMP	-0.198***	-0.178***	-0.151***	-0.149***
	(0.052)	(0.052)	(0.017)	(0.015)
R-Square	0.054	0.056	0.036	0.045
Observations	2,749,701	2,261,260	21,113,962	20,594,947

Notes: Coefficients of logit regression for probability of an individual diagnosed with abuse/addiction of prescription opioid. Individual controls include age, gender, education, income and type of insurance. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 9: Effect of PDMP on probability of abuse by income category

	Income					
	(1) Less than 40K	*(2) 40-49K*	*(3) 50-59K*	*(4) 60-75K*	*(5) 75-99K*	*(6) 100K+*
PDMP	-0.185**	-0.102	-0.129**	-0.107	-0.069	-0.062
	(0.074)	(0.077)	(0.064)	(0.066)	(0.071)	(0.041)
Controls:						
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.043	0.030	0.031	0.032	0.038	0.047
Observations	7,389,628	5,292,648	5,313,836	6,727,332	8,994,455	15,026,741

Notes: Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of prescription opioid for different income groups. Individual controls include age, education, gender, type of insurance. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 10: PDMP effect on probability of abuse by education level

	Education			
	(1) Less than 12th grade	*(2) High school diploma*	*(3) Less than bachelor degree*	*(4) Bachelor degree plus*
PDMP	-0.011	-0.119*	-0.158*	-0.175**
	(0.277)	(0.069)	(0.086)	(0.088)
Controls:				
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Ind. Controls	Yes	Yes	Yes	Yes
R-Square	0.055	0.042	0.040	0.041
Observations	347,537	17,141,161	29,477,892	9,337,854

Notes: Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of prescription opioid for different education level. All specifications control for other individual characteristics including age, gender, income and type of insurance in addition to state and year fixed effects. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 11: Effect of PDMP on probability of abuse by type of insurance

	Insurance				
	EPO	*HMO*	*IND*	*POS*	*PPO*
PDMP	-0.120**	-0.209***	-0.391	-0.036	0.026
	(0.047)	(0.053)	(0.321)	(0.029)	(0.149)
Controls:					
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Ind. Controls	Yes	Yes	Yes	Yes	Yes
R-Square	0.044	0.057	0.109	0.036	0.036
Observations	6,931,178	16,550,381	159,186	34,051,197	4,888,403

Notes: Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of prescription opioid for different insurance. All specifications control for individual characteristics including age, gender, income and education in addition to state and year fixed effects. Robust standard errors, clustered at the state level, in parentheses. * p <0.10, ** p <0.05, *** p<0.01

Table 12: Relationship between narcotic prescription and event of opioid abuse/dependence

		Ever abused opioids?	
		No	*Yes*
Ever been prescribed opioids?	*No*	69.22	0.08
	Yes	30.42	0.28
Pr(abuse | prescribed)=		0.92%	
Pr(abuse | not prescribed)=		0.12%	
Pr(not prescribed | abuser)=		22.98%	

Notes: Dataset includes the medical and prescription claims of around 19 million people in 25 states between 2001-2012. The abuse indicator is Yes if they have ever been diagnosed with any prescription opioid abuse/addiction, and the narcotic indicator is Yes if they have ever been prescribed any form of narcotics.

Table 13: Effectiveness of the PDMP for patients with prescription vs. patients without prescription

	(1) w prescription	*(2) w/o prescription*
PDMP	-0.105**	-0.077
	(0.048)	(0.079)
ln(mme+1)	-0.036**	
	(0.014)	
ln(day_sup+1)	0.684***	
	(0.023)	
Controls:		
State FE	Yes	Yes
Year FE	Yes	Yes
Ind. Controls	No	No
R-Square	0.132	0.025
Observations	18,936,921	42,830,641
Percent Mean	0.378	0.059

Notes: Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of prescription opioid. With state and year fixed effects. State level clustered standard errors. rx=1 if there is any record of opioid prescription in the medical record. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01.

Table 14: Summary statistics: Outcomes among opioid takers

	Mean	Median	99th Percentile
Mean Daily MME	6.67	0.62	129.15
Mean MME per Prescription	60.75	36	800
Total Days of supply	32.55	6	462
Number of Prescriptions	2.75	1	24
Number of Prescribers	1.34	1	5
Number of Pharmacies	1.24	1	4

Notes: Summary statistics of misuse proxy measures, constructed similar to Buchmueller and Carey (2017) .

Table 15: Correlation of outcomes among whole population

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
(1) 391+ Days Supply	1				
(2) 120+ Daily MME	0.585	1			
(3) 10+ Pharmacy	0.093	0.065	1		
(4) 10+ Provider	0.089	0.050	0.382	1	
(5) Opioid abuse	0.094	0.093	0.061	0.080	1

Notes: Pairwise correlations for measures of misuse. All the numbers are significant in 0.001 level.

Table 16: The effect of PDMP on prescribed opioids

	(1) *mme*	(2) *ln(mme+1)*	(3) *Sch2 mme*	(4) *ln(Sch2 mme+1)*	(5) *Sch3 mme*	(6) *ln(Sch3 mme+1)*
PDMP	-41.307	0.016	-41.326	0.016	-0.649***	-0.005*
	(30.687)	(0.016)	(31.257)	(0.015)	(0.193)	(0.003)
R-Square	0.000	0.004	0.000	0.006	0.000	0.002
Observations	61,767,467	61,767,467	61,767,491	61,767,475	61,767,491	61,767,487
Mean	426	0.934	407	0.800	5.625	0.096

Notes: The dependent variable in (1) is the total mme in each year for each individual. The dependent variable in (2) is the log transformation of the mme+1. The dependent variable is (3) is schedule 2 share of total mme, the dependent variable in (4)is the log transformation of schedule 2 mme+1. Similarly, dependent variables in (4) and (5) are the schedule 3 mme and its log transformation. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 17: Effectiveness of PDMPs on opioid misuse

	P(taking opioids)	*120+ daily mme*	*391+ days' supply*	*10+ pharmacy*	*10+ providers*	*Opioid abuse*
PDMP	0.167	-0.298	-0.186*	-0.034*	-0.090	-0.183*
	(0.391)	(0.177)	(0.094)	(0.017)	(0.066)	(0.104)
R-Square	0.910	0.906	0.928	0.764	0.868	0.862
Observations	300	300	300	300	300	300
Weighted Mean	16.204	1.246	1.663	0.069	0.189	0.826

Notes: Dependent variables are constructed similar to Buchmueller and Carey (2017). All regressions have year and state fixed effects with the number of observations in each state-year. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p <0.05, *** p<0.01

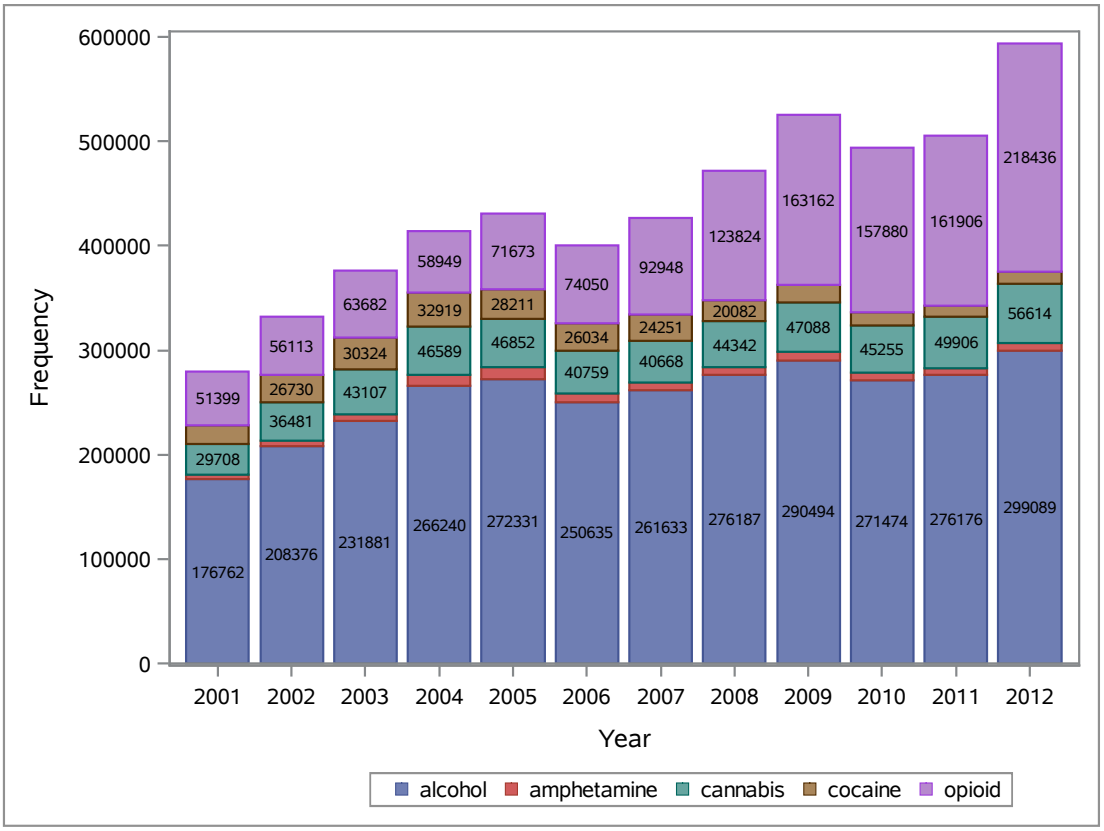
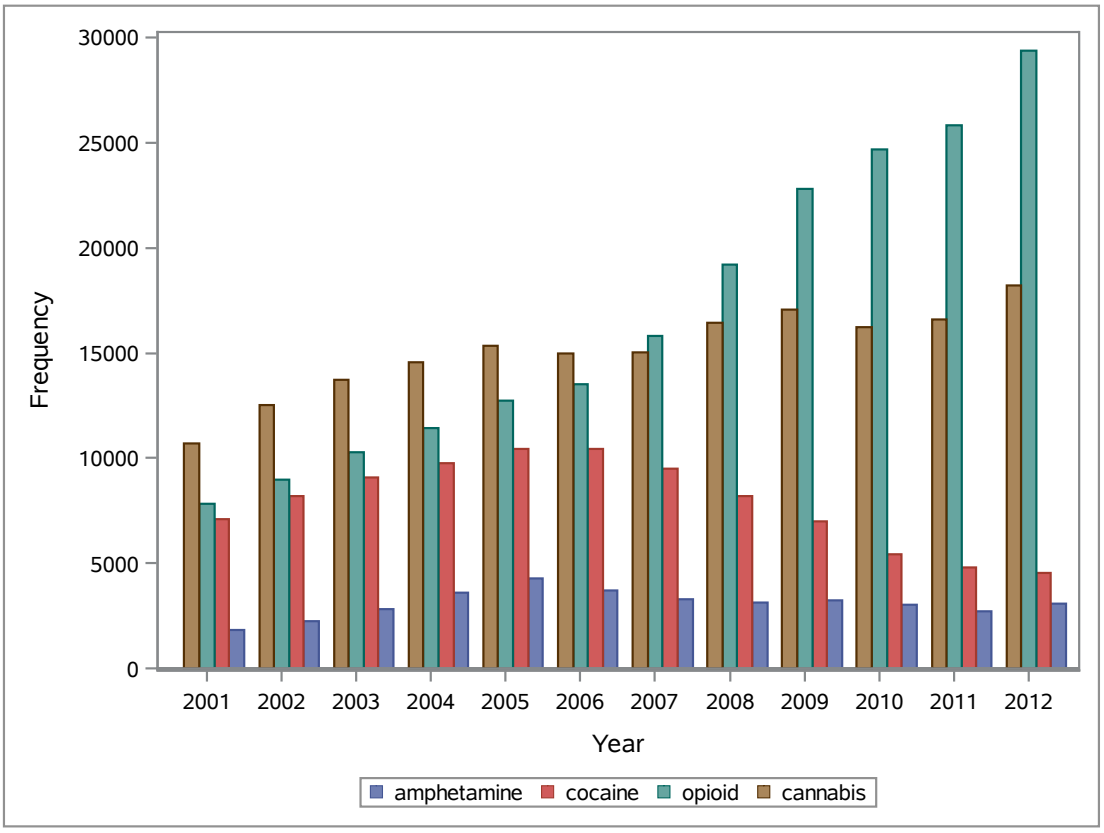
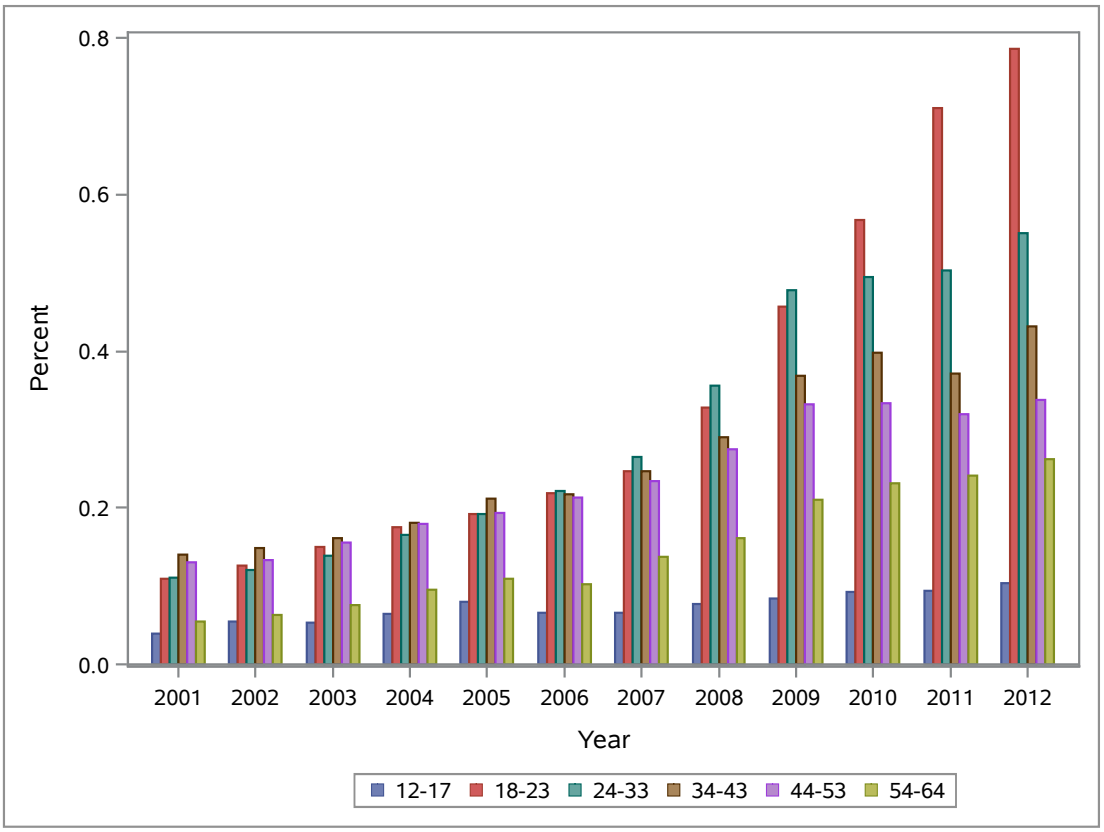


Figure 1: Number of visits for abuse/dependence by substance category



Notes: The numbers show the frequency of visits related to each substance abuse/dependence during 2001-2012 over 50 states.

Figure 2: Total number of people who visit any inpatient/outpatient facilities for each substance



Notes: Each bar represents the percentage of people in each age-year category that abused prescription opioids

Figure 3: Trend in abuse of prescription opioids by age category in 25 states

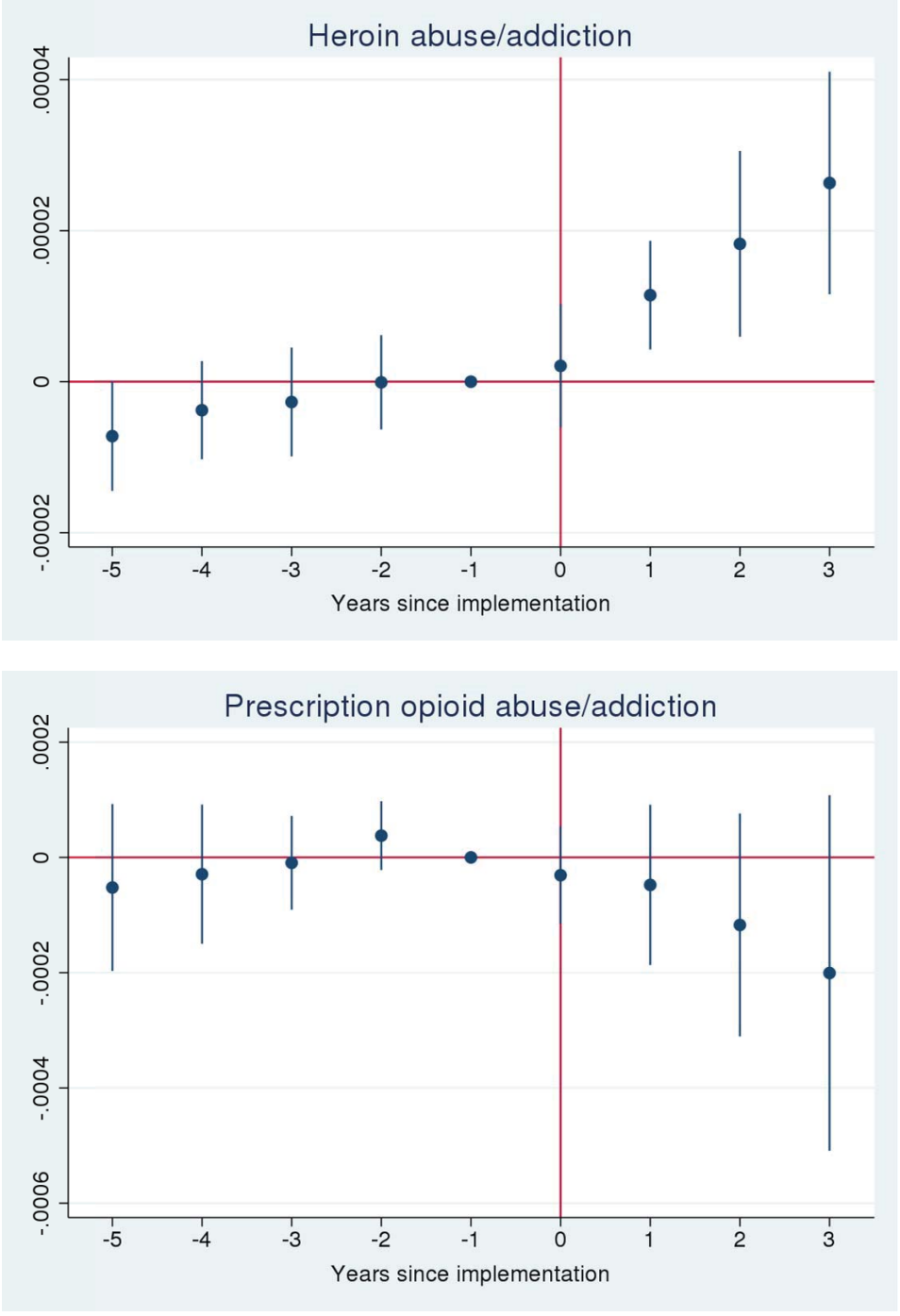
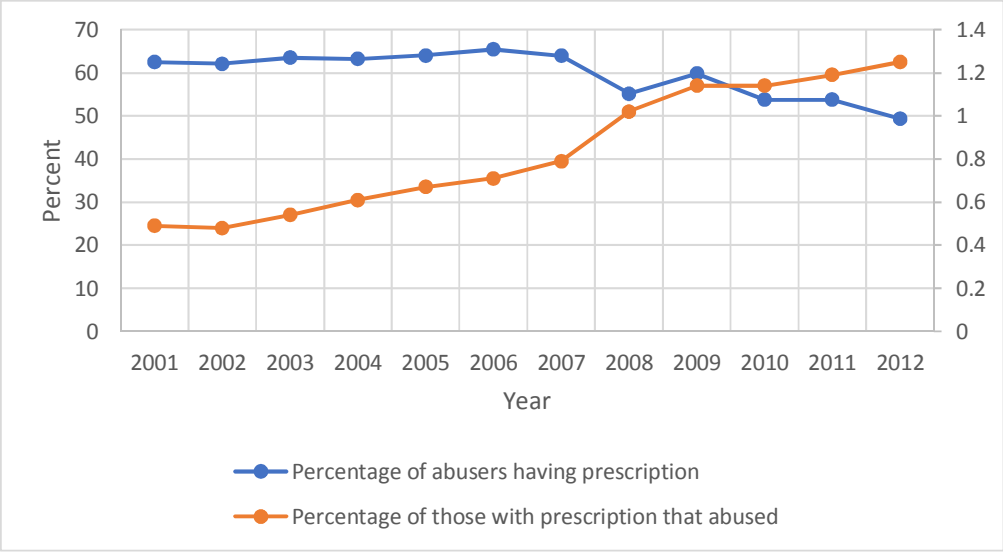


Figure 4: Probability of prescription opioid abuse/dependence 4 years after and before the implementation of PDMPs



Notes: Left axis and blue line: It shows the percentage of abusers that filled any prescription for opioids.
Right axis and orange line: It shows the percentage of the patients with opioid prescription that have a record of abuse/addiction of opioids in that year.

Figure 5: Relationship between narcotic prescription and event of abuse/dependence from 2001-2012

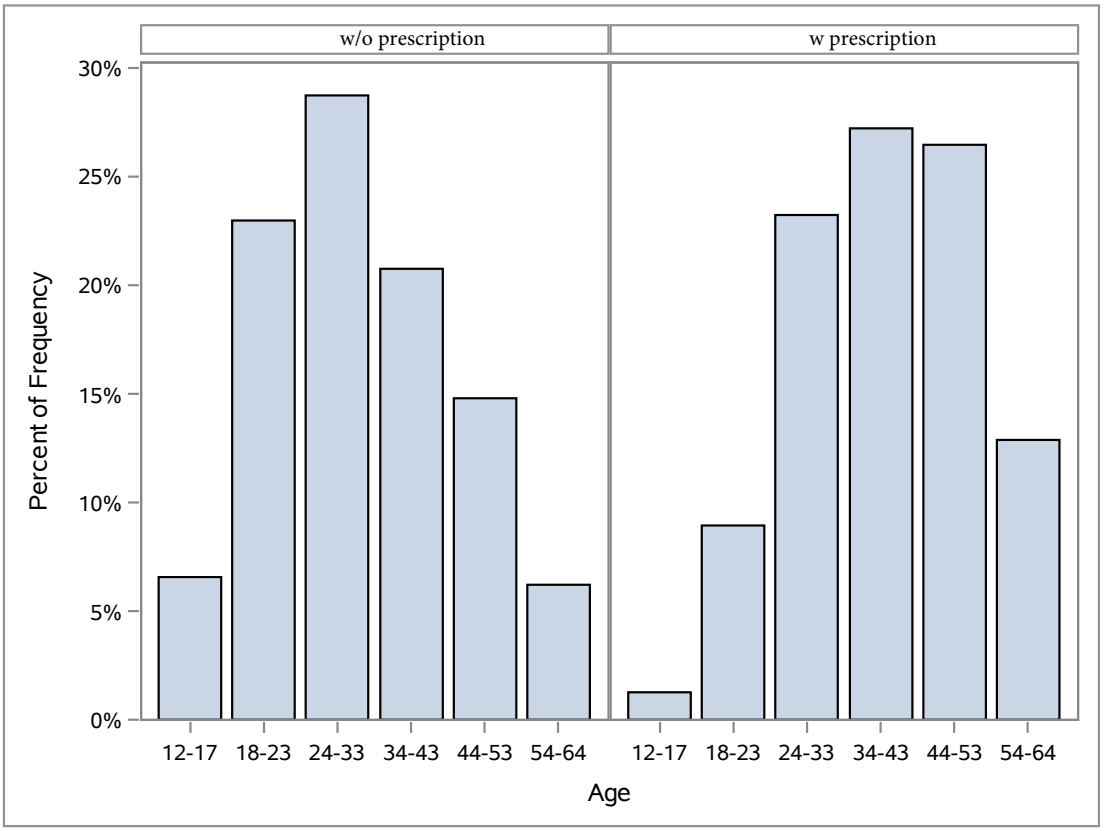


Figure 6: Age distribution of abuser population by source of drug

References

Ballantyne, J. C. and Mao, J. (2003), 'Opioid therapy for chronic pain', *New England Journal of Medicine* **349**(20), 1943–1953.

Blumenschein, K., Fink, J., Freeman, P., James, K., Kirsh, K., Steinke, D. and Talbert, J. (2010), 'Review of prescription drug monitoring programs in the United States', *Institute for Pharmaceutical Outcomes and Policy, Department of Pharmacy Practice and Science, College of Pharmacy, University of Kentucky, Lexington, Kentucky* pp. 1–28.

Buchmueller, T. C. and Carey, C. (2017), 'The effect of prescription drug monitoring programs on opioid utilization in medicare'.

Dunn, K. M., Saunders, K. W., Rutter, C. M., Banta-Green, C. J., Merrill, J. O., Sullivan, M. D., Weisner, C. M., Silverberg, M. J., Campbell, C. I., Psaty, B. M. et al. (2010), 'Opioid prescriptions for chronic pain and overdose: A cohort study', *Annals of Internal Medicine* **152**(2), 85–92.

Fink, R. (2000), 'Pain assessment: the cornerstone to optimal pain management', *Proceedings (Baylor University. Medical Center)* **13**(3), 236.

Finklea, K., Sacco, L. N. and Bagalman, E. (2014), 'Prescription drug monitoring programs', *Journal of Drug Addiction, Education, and Eradication* **10**(4), 481.

Furlan, A. D., Sandoval, J. A., Mailis-Gagnon, A. and Tunks, E. (2006), 'Opioids for chronic noncancer pain: a meta-analysis of effectiveness and side effects', *Canadian Medical Association Journal* **174**(11), 1589–1594.

Haegerich, T. M., Paulozzi, L. J., Manns, B. J. and Jones, C. M. (2014), 'What we know, and don't know, about the impact of state policy and systems-level interventions on prescription drug overdose', *Drug and alcohol dependence* **145**, 34–47.

Hedegaard, H., Warner, M. and Miniño, A. (2017), 'Drug overdose deaths in the United States, 1999-2015', *NCHS data brief* .

Højsted, J. and Sjøgren, P. (2007), 'Addiction to opioids in chronic pain patients: a literature review', *European Journal of Pain* **11**(5), 490–518.

Kilby, A. (2016), Opioids for the masses: Welfare tradeoffs in the regulation of narcotic pain medications, *in* '2016 Fall Conference: The Role of Research in Making Government More Effective', Appam.

Kolodny, A., Courtwright, D. T., Hwang, C. S., Kreiner, P., Eadie, J. L., Clark, T. W. and Alexander, G. C. (2015), 'The prescription opioid and heroin crisis: a public health approach to an epidemic of addiction', *Annual review of public health* **36**, 559–574.

Martell, B. A., O'Connor, P. G., Kerns, R. D., Becker, W. C., Morales, K. H., Kosten, T. R. and Fiellin, D. A. (2007), 'Systematic review: Opioid treatment for chronic back pain: Prevalence, efficacy, and association with addiction', *Annals of Internal Medicine* **146**(2), 116–127.

McCabe, S. E., Cranford, J. A., Boyd, C. J. and Teter, C. J. (2007), 'Motives, diversion and routes of administration associated with nonmedical use of prescription opioids', *Addictive behaviors* **32**(3), 562–575.

McCabe, S. E., Cranford, J. A. and West, B. T. (2008), 'Trends in prescription drug abuse and dependence, co-occurrence with other substance use disorders, and treatment utilization: Results from two national surveys', *Addictive Behaviors* **33**(10), 1297–1305.

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

of Excellence, P. M. P. C. (2012), 'Briefing on PMP Effectiveness–Prescription Monitoring Programs: An Effective Tool in Curbing the Prescription Drug Abuse Epidemic'.

of Excellence, P. M. P. C. (2014), 'Briefing on pdmp effectiveness'.

Paulozzi, L. J. (2012), 'Prescription drug overdoses: A review', *Journal of Safety Research* **43**(4), 283–289.

Pletcher, M. J., Kertesz, S. G., Kohn, M. A. and Gonzales, R. (2008), 'Trends in opioid prescribing by race/ethnicity for patients seeking care in US emergency departments', *JAMA* **299**(1), 70–78.

Portenoy, R. K. (1996), 'Opioid therapy for chronic nonmalignant pain: A review of the critical issues', *Journal of Pain and Symptom Management* **11**(4), 203–217.

Portenoy, R. K. and Foley, K. M. (1986), 'Chronic use of opioid analgesics in non-malignant pain: Report of 38 cases', *Pain* **25**(2), 171–186.

SAMHSA (2014*a*), 'Results from the 2013 national survey on drug use and health: Summary of national findings, nsduh series h-48, hhs publication no. (sma) 14-4863'.

SAMHSA (2014*b*), 'Treatment episode data set (teds): 2002–2012. national admissions to substance abuse treatment services. bhsis series s-71, hhs publication no.(sma) 14-4850'.

White, A. G., Birnbaum, H. G., Schiller, M., Tang, J. and Katz, N. P. (2009), 'Analytic models to identify patients at risk for prescription opioid abuse.', *The American Journal of Managed Care* **15**(12), 897–906.

Zenz, M., Strumpf, M. and Tryba, M. (1992), 'Long-term oral opioid therapy in patients with chronic nonmalignant pain', *Journal of pain and symptom management* **7**(2), 69–77.