The impact of information in health care markets: prescription drug monitoring programs and abuse of opioid pain relievers

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Abstract:

Overdose deaths, substance abuse treatment admissions, and emergency department visits involving opioid pain relievers have increased sharply in the last decade. In response, many states have implemented prescription drug monitoring programs (PDMPs), electronic databases that track the prescribing and dispensing of controlled substances. The main intent of these programs is to inform treatment decisions and identify and prevent "doctor shopping" and illicit prescribing or dispensing. This paper investigates the impact of state prescription drug monitoring programs on the abuse of opioid pain relievers, measured by non-medical use of prescription pain relievers, substance abuse treatment admissions for opioid abuse and opioid overdose deaths. I estimate difference-in-differences models in which I use variation in the timing of PDMP implementation across states as a source of exogenous variation in exposure to the program to identify impacts of PDMPs. I address possible policy endogeneity by controlling for pre-implementation trends as well as seven other types of state laws that are likely to affect prescription drug abuse and diversion. The preferred estimates suggest that PDMPs reduced opioid abuse treatment admissions by 13.1%. I also find suggestive evidence that PDMPs reduced non-medical use of prescription pain relievers and Oxycontin at the intensive margin.

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1. Introduction

Overdose deaths involving opioid pain relievers have quadrupled since 1999, and now exceed the sum of deaths involving heroin and cocaine (Centers for Disease Control and Prevention, 2011). Emergency department visits and substance abuse treatment admissions for opioid pain reliever abuse have also increased sharply over the last decade. Figure 1 shows trends in overdose deaths, substance abuse treatment admissions, and emergency department visits resulting from opioid abuse or misuse. Opioid pain relievers are a class of drugs that includes oxycodone (e.g. OxyContin, Percocet), hydrocodone (e.g. Vicodin), morphine, codeine, methadone, fentanyl, meperidine (e.g. Demerol), and tramadol.[1] These drugs are naturally derived from, or are synthetic versions of, opium. This paper investigates the impact of state prescription drug monitoring programs on opioid pain reliever abuse and related health outcomes (substance abuse treatment admissions and overdose deaths).

Opioid pain relievers have long been used to relieve acute pain, such as post-surgery or cancer pain, while non-narcotic pain relievers such as acetaminophen, aspirin, and other non-steroidal anti-inflammatory drugs (NSAIDS) are used to treat mild to moderate pain. Since the early 1990s, opioids have been increasingly used to treat chronic non-cancer pain, partly as a result of liberalization of prescribing laws by state medical boards, introduction of new pain management standards by the Joint Commission on the Accreditation of Healthcare Organizations (JCAHO) in 2000, an increased awareness among patients of the right to pain relief, and aggressive marketing by the pharmaceutical industry (Manchikanti et al., 2012). The rise in overdoses involving opioid pain relievers in the US parallels the rise in the total amount of

[1] While oxycodone is perhaps the most well known and frequently abused opioid pain reliever, the term “opioid pain reliever” refers to a large category of drugs, including semi-synthetic opioids such as morphine, codeine, and hydrocodone, and synthetic opioids like methadone and fentanyl. These drugs can all be obtained from retail pharmacies in pill form with a prescription, and are all used for pain relief. The inclusion of methadone in this category refers to its use as a prescription pain reliever, and not as a treatment for heroin addiction.

pain relievers prescribed over time. Opioids produce a feeling of euphoria and ongoing use may lead to physical dependence, while non-narcotic pain relievers like acetaminophen, aspirin, and other NSAIDS do not have this side effect. In this paper, I define abuse of opioid pain relievers as “nonmedical use,” i.e., use of the medication in any way not intended by the prescribing doctor. This includes use of the medications for reasons or in dosages other than as prescribed, including simply for the feeling produced by the drugs. An opioid overdose results from taking too large of a dose or from a drug interaction with alcohol or other drugs such as benzodiazepines (e.g. Valium, Xanax). Other symptoms of opioid abuse include extreme lethargy, nausea, confusion or poor judgment, and reduced drive.

Imperfect information in the market for opioid pain relievers may lead to the prescribing of more drugs than is appropriate, or prescribing to individuals who do not have a legitimate need for these medications. For instance, doctors often cannot verify whether a patient’s complaint about pain is legitimate or if the patient is abusing the drugs. An insurer covers prescriptions but does not know if the doctor is needlessly or even fraudulently prescribing. Prescription drug monitoring programs (PDMPs) are a policy response that attempts to address rising rates prescription drug abuse and associated adverse outcomes by curbing overprescribing through the provision of information. PDMPs are intended to inform treatment decisions and deter drug abuse, misuse, and diversion. In particular, they aim to prevent “doctor shopping”, a practice where patients who are addicted to prescription drugs or who intend to resell them visit multiple doctors in order to obtain multiple prescriptions for drugs. PDMPs also aim to deter excessive or fraudulent prescribing by any given doctor.

The key requirement of any PDMP is that retail pharmacists must enter into an electronic database the following data from prescriptions of controlled substances: identifying information for the prescriber, dispenser, and patient, the medication name, the dose and the amount. Most states require reporting of the prescription data within 7-14 days. Doctors and pharmacists who are authorized to access the PDMP can view the prescription history of their patients via a website prior to prescribing. A physician or pharmacist who checks the PDMP data and sees that a particular patient is a likely doctor shopper or addict can decline to write or fill prescriptions for them, and she can encourage the patient to seek treatment. PDMP data can also allow state personnel to identify individuals who are prescribing or dispensing inappropriately, or who are doctor shopping.

Currently, forty-six states have operational PDMPs, while two more have passed legislation to implement one. In 2002 only fifteen states had operational PDMPs. While PDMPs have a long history (see section 2), I focus on the most recent wave of implementation that occurred from 1997-2013. I use variation in the timing of implementation across states as a source of exogenous variation in exposure to a PDMP to identify impacts on nonmedical use, treatment admissions, and overdose deaths. I use multiple public use and restricted-access datasets to construct several measures of health outcomes. I also collect data on PDMP implementation dates as well as several other types of laws relevant to prescription drug abuse. Because PDMPs restrict access to opioids, I hypothesize that PDMPs should reduce rates of nonmedical use and overdose deaths. However, with treatment admissions, the effect of the policy is ambiguous. Restricting drugs could increase admissions as addicts cannot get drugs and need help quitting. Alternatively it may decrease admissions because there are fewer addicts. It is possible that PDMPs increase admissions in the short run but decrease them in the long run. Using a difference-in-differences approach, I find that PDMPs reduced substance abuse treatment admissions for opioids by 13.1%. I also find suggestive evidence that it may have reduced prescription pain reliever and Oxycontin use at the intensive margin. I do not find that PDMPs have a statistically significant effect on total overdose deaths. I also do not find strong evidence of substitution to heroin or marijuana.

2. Prescription Drug Monitoring Programs

PDMP implementation has occurred over three distinct waves. The earliest programs were paper prescription tracking programs implemented in ten states prior to 1990. These first-generation PDMPs did not provide reports to prescribers or pharmacists. The data collected by these programs were primarily used by law enforcement personnel investigating fraudulent prescribing (Prescription Drug Monitoring Program Center of Excellence, 2012). The second wave of PDMPs was implemented in twelve states from 1990-2003. These laws called for the collection of prescription data for Schedule II[2] substances electronically, without the use of multiple-copy prescription forms. Like the old paper programs, these early electronic PDMPs were intended primarily for use by law enforcement. As before, practitioners typically did not have online access to the data, and therefore they could not use the data to inform treatment decisions or identify doctor shoppers. (Prescription Drug Monitoring Program Center of Excellence, 2012).

The third wave of implementation, which is the focus of this paper, occurred from 1997-2013. Thirty-eight states implemented a PDMP for the first time within this period, and eleven of the twelve states with the early electronic programs described above also upgraded their PDMPs

[2] The Controlled Substances Act (CSA) of 1970 is the federal US drug policy under which manufacture, importation, possession, use and distribution of certain substances is regulated. This legislation created five Schedules (classifications), with different criteria for substances to be included in each. Schedule I contains substances with no currently accepted medical use and cannot safely be made available to the public with a prescription. Schedules II-V contain substances that have recognized medical uses and can be manufactured, distributed and used in accordance with the CSA. The order of the schedules reflects substances that are progressively less dangerous and addictive. Opioid pain relievers such as oxycodone, morphine, and methadone are in Schedule II, while other opioids (eg. Vicodin, a combination of hydrocodone and acetaminophen) are in Schedule III or higher.

in this time periods. These PDMPs typically allow prescribers and dispensers to access the prescription data directly via a website, collect data on a larger number of drugs (Schedules II-III or higher), and require weekly or bi-weekly reporting. The most important difference between the third wave PDMPs and earlier versions is that doctors are able to access the PDMP data prior to prescribing. This feature is key to addressing the problem of imperfect information and reducing overprescribing. Table A.1 in the appendix shows dates of the third wave of PDMP implementation by state.

All PDMPs require pharmacists to report prescription data periodically, and failure to do so may result in the pharmacist losing her license and incurring other legal penalties. However, other program requirements vary substantially by state. For example, some states provide unsolicited reports to doctors and pharmacists about patients who the PDMP suspects of engaging in doctor-shopping, while other states do not. The thresholds which PDMPs use to identify suspected doctor- shoppers also vary by state. These thresholds typically are in the form of a specific number of prescribers or pharmacists who filled prescriptions for the patient in a given time period (1-6 months, depending on the state). Whether law enforcement agencies have direct access to the PDMP data or whether they can only access it during an ongoing investigation also varies by state. While these are important differences in program functioning, this paper focuses on estimating the average effect of having a PDMP on health outcomes.

There is a small public health literature on prescription drug monitoring programs. To my knowledge, there is only one published study – Paulozzi et al (2011) - that uses a differences-in-differences model (i.e. fixed effects panel regression) to evaluate the impact of PDMPs on abuse. This study finds that PDMP presence is not associated with lower rates of drug overdose or opioid overdose mortality. Reifler et al (2012) study the association of PDMPs with measures of opioid abuse constructed using data from the RADARS System Poison Center and Opioid Treatment surveillance databases. The data consists of intentional cases of opioid abuse and misuse gathered from participating poison centers and methadone treatment programs. The authors find that PDMPs are associated with reductions in rates of opioid abuse. A limitation of this study is that it does not control for state and year fixed effects in the estimated models. Instead, it controls for a linear time trend and models state effects as random effects. In this case, the coefficient on PDMP is identified using both within and between state variation. Time invariant differences across states that may be correlated with PDMP implementation are not controlled for, and may be a source of bias for the estimated effect of PDMPs in this study. Reifler et al (2012) also include a control for local opioid availability that is likely to be endogenous to the treatment variable. Simeone and Holland (2006) use the Treatment Episodes Data Set from 1997-2003, and the ARCOS dataset on supply of controlled substances. They find PDMP presence is associated with lower supply of opioids but no significant differences in treatment admissions. Like Reifler et al (2012), this study also controls for linear time trend and random state effects instead of state and year fixed effects. All three studies analyze relatively short time periods and do not control for other relevant policies that may affect abuse.

The main contribution of my study to the literature is to estimate the impact of prescription drug monitoring programs on a wide variety of outcomes using multiple large, nationally representative datasets, including two restricted-access datasets. I analyze a longer time period than has previously been studied. I also perform a more comprehensive analysis of related policies by collecting data on and controlling for a number of related state laws that if omitted may bias the estimates of PDMP impact. In addition, I investigate effects of PDMPs on two potential substitutes to opioids – heroin and marijuana.

This paper also relates to the broader literature on policies restricting access to addictive substances, including the minimum legal drinking age (Cook and Moore, 2001; Carpenter et al., 2007; DiNardo and Lemieux, 2001), laws barring youth purchase or use of tobacco (Tauras et al., 2005), indoor smoking bans (Bitler et al., 2010), legal penalties for drug purchase and possession (Chaloupka et al.,1999; Saffer and Chaloupka, 1999), methamphetamine precursor restrictions (Dobkin and Nicosia, 2009), and other increases in drug law enforcement (Weatherburn et al.,2002). PDMPs are another example of a supply-side intervention that aims to reduce abuse.

3. Data

To study the effects of PDMPs on self-reported drug use, I use the restricted-access National Survey of Drug Use and Health (NSDUH) with state identifiers. The NSDUH is a nationally representative survey of noninstitutionalized US individuals aged 12 or older, and is a repeated cross-section. The survey is conducted through in-person interviews. The data contain detailed information about respondents' use of drugs, alcohol and tobacco, as well as detailed demographic characteristics, and are available for years 2004 to 2011. The two outcomes I study are nonmedical use of prescription pain relievers and nonmedical use of Oxycontin. The prescription pain relievers category includes both opioid pain relievers as well as other prescription drugs that are used for pain relief. Because this measure captures some nonmedical use of non-opioid drugs, I also analyze Oxycontin use specifically. I look at lifetime, past year, and past month use, as well as the number of days the respondent used the drug nonmedically in the past year and per month in the past year. The NSDUH data are merged to the policy data on lagged year. A limitation of the NSDUH is that the data are self-reports of drug use. If respondents do not answer honestly or do not recall past events correctly, some underreporting and overreporting will take place. For instance, social desirability bias may lead respondents to underreport nonmedical use of pain relievers.

To study substance abuse treatment admissions, I use the Treatment Episodes Data Set (TEDS). The TEDS contains information on the number and characteristics of persons admitted to substance abuse treatment programs that receive public funding from 1992-2010. The data contain each state's administrative data on treatment admissions that are collected by the Substance Abuse & Mental Health Service Administration (SAMHSA) and standardized to be consistent across states. Variables include year and state of admission, substances abused, nature of treatment, and patient characteristics. For each admission record, the data indicates the primary, secondary, and tertiary substances of abuse. I define an admission for opioid abuse as one that has either "Other opiates and synthetics" or "Non-prescription methadone" as one of the reported substances. This definition includes admissions for oxycodone, hydrocodone, codeine, hydromorphone, meperidine, morphine, tramadol, methadone and other drugs with morphine-like effects. Heroin is not considered an opioid pain reliever. Of the 1.9 million opioid abuse admissions, 93.4% have a mention of "Other opiates and synthetics" and 8.7% have a mention of non-prescription methadone. I collapse the data to counts of admissions at the state-year level.

One limitation of the TEDS data is the truncation of the number of substances reported at admissions at three substances, rather than reporting the exhaustive list of substances. 20.7% of all admissions in the TEDS had three substances reported at admission, which suggests that many patients may have been using more than three substances. However, this top-coding of the number of substances will only bias results if it is correlated with the timing of PDMP implementation, which is unlikely. Also, capacity constraints imply that if treatment facilities are full, an increase in opioid admissions leads mechanically to fewer admissions for other substances. This problem can be addressed in part by controlling for supply of treatment facilities. Another limitation is that the TEDS records information on patients at federally funded treatment facilities only, and lacks information on admissions to private treatment facilities. However, as nearly all treatment facilities receive some federal funds, the TEDS constitutes a near census of all substances abuse treatment admissions in the US. Note that the TEDS data are missing for certain years and states (40 observations), because in some years states did not report usable data.

For data on US drug overdose deaths, I use the 1999-2010 Multiple Cause Mortality data files from the National Vital Statistics System. These data include records of every death that occurred in the US from 1999-2010, with state and county of death and residence, month of death, race, age, sex, and detailed cause of death information. These data are collected individually by states, and then reported to the National Center for Health Statistics (NCHS), which standardizes the data to be consistent across states. While mortality data are available for years prior to 1999, a change in the cause of death classification system in 1999 limits comparability of the post-1999 period to earlier years. From 1979-1998, cause of death was categorized using the 9th revision of the International Classification of Diseases (ICD-9 codes). From 1999 to 2010, ICD-10 codes were used. This change presents a challenge as the correspondence between the ICD-9 and ICD-10 coding systems are imperfect. The CDC's published studies of opioid overdoses use data from 1999 onwards only (Centers for Disease Control and Prevention (2011), Paulozzi et al. (2011)). To be consistent with these studies, I restrict my analyses to years 1999-2010 as well. I analyze total opioid deaths as well as unintentional overdose deaths, suicides and opioid overdose deaths of undetermined intent separately. Table A.2 in the appendix lists the ICD-10 codes used to categorize overdose deaths. As with the TEDS, I collapse the mortality data to counts of deaths at the state-year level.

I merge both the TEDS and mortality data with population data from the Surveillance Epidemiology and End Results (SEER) Program to compute state-level rates of opioid admissions and opioid overdoses per 100,000 population. I also use the SEER data to compute age group shares, percent male, Hispanic, black and other race for each state and year. In addition, I merge average state unemployment rates from the Bureau of Labor Statistics and state median household income and health insurance coverage from the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC). The CPS ASEC data are merged on lagged year because the ASEC survey is conducted in March and captures the previous year's income and insurance data.

The PDMP enactment and operational start dates were obtained in part from the National Alliance of Model State Drug Laws (NAMSDL). The operational start date is defined as the date the PDMP started collecting data. As the NAMDSL data were incomplete for several states with older programs, I obtained the missing dates by individually contacting state PDMP administrators and searching legal databases and the PDMPs' websites to collect all relevant dates for each state.

I also collected data on other state laws that might affect opioid abuse. I used the CDC Public Health Law Program's compilation of legal citations for seven types of state legislative strategies that govern prescription drug abuse and diversion in the US (Centers for Disease Control and Prevention, 2012.) The seven law types are 1) laws regulating pain clinics, 2) laws prohibiting "doctor shopping"/fraud, 3) laws setting prescription drug limits, 4) laws requiring a physical examination before prescribing, 5) laws requiring tamper-resistant prescription forms,

6) laws requiring patient identification before dispensing, and 7) laws providing immunity from prosecution/mitigation at sentencing for individuals seeking assistance during an overdose. As the CDC only compiled the legal citations for these laws, but not enactment and effective dates, I collected these dates by searching Westlaw and Lexis-Nexis legal databases. In cases where multiple laws existed for a given state and legal category, I used the dates of the earliest implemented law in my analyses. Table 1 shows the correlation matrix for PDMPs and the seven other law categories. Presence of a PDMP is not highly correlated with any of the seven other law categories. The correlation between doctor-shopping laws and pain clinic laws is the largest, with a correlation coefficient of 0.45. The correlation coefficients for the doctor-shopping law and ID requirement law, and the pain clinic and ID requirement laws, are similarly large at 0.38 and 0.35, respectively.

4. Empirical strategy

I use variation across states and time in the implementation of prescription drug monitoring programs to identify the effect of PDMPs on nonmedical pain reliever and Oxycontin use, opioid treatment admissions, and overdose deaths. I estimate difference-in-difference models as follows:

(1) $$y_{ist} = \alpha + \beta_1(PDMP)_{st} + X'_{st}\beta_2 + X'_{ist}\beta_3 + \gamma_s + \delta_t + \varepsilon_{ist}$$

(2) $$y_{st} = \alpha + \beta_1(PDMP)_{st} + X'_{st}\beta_2 + \gamma_s + \delta_t + \varepsilon_{st}$$

Where $(PDMP)_{st} = 1\{state\ s\ in\ year\ t\ has\ an\ operational\ PDMP\}$

Equation (1) is estimated using individual-level data from the National Survey of Drug Use and Health, while equation (2) is estimated using treatment admissions and mortality data aggregated to the state-year level. *s* indexes the state, and *t* indexes the year. I control for state fixed effects (γ_s) and year fixed effects (δ_t) in all models. The treatment variable, $PDMP_{st}$, is set equal to 0 in all years prior to the year of implementation, and set equal to 1 in all years post-implementation. In the year of program implementation, $PDMP_{st}$ is set equal to the fraction of the year for which program was operational. In equation (1), y_{ist} represents lifetime, past year, and past month use of pain relievers and Oxycontin in state *s* at time *t*. I also estimate models of frequency of use conditional on nonmedical use in the past year. The vector of individual-level control variables in equation (1), X_{ist}, includes gender, race/ethnicity, age groups (12-17, 18-24, 35-44, 45-54, 55-64, and 65+ years), family income ranges (less than $20K, $50-74.9K, and $75K and above), household size, and indicators for health insurance coverage and living in a non-metropolitan county. The state-level controls in equation (1) include the seven law categories. In equation (2), y_{st}, represents the natural log of opioid admissions or overdose deaths in state s at time t. The vector of state-year characteristics in equation (2), X_{st}, includes log total state population, state population shares of males, blacks, other race (not white or black), Hispanics, and age groups (0-14, 15-24, 35-44, 45-54, 55-64, 65+), average state unemployment rate, state median household income, percent of state with health insurance coverage, and the seven other laws that may impact prescription drug abuse. Standard errors are clustered at the state level.

The parameter of interest in equations (1) and (2) is β_1, which provides a difference-in-difference estimate of the effect of PDMP implementation on the outcomes of interest. I expect the true value of β_1 to be less than or equal to zero, i.e., that the program will have a negative or null effect on abuse. Identification of β_1 hinges on PDMP implementation being uncorrelated with unobserved determinants of opioid pain reliever abuse. One threat to identification is policy endogeneity - unobserved factors that are correlated with both PDMP implementation and opioid abuse (Besley and Case, 2000). If these factors are time-invariant, then controlling for state fixed effects will remove them. Also, the year fixed effects absorb nationwide trends, i.e., they account for the fact that average rate of abuse and overdose in the US are increasing over time. What would be problematic for identification is any state-specific trend in abuse and overdose rates that is correlated with PDMP implementation. An example of selection into the program that would bias β_1 is if states with rapidly rising overdose or abuse rates implement PDMPs in response to this trend. In this case, omitted variables are positively correlated with both abuse/overdoses and PDMP implementation. As a result, the estimate of $\beta_1$would be biased upwards, i.e. in the direction that suggests a smaller effect of PDMP implementation than is actually the case. Another type of selection is if states that are implementing stricter prescribing laws or increasing enforcement are more likely to implement a PDMP. In this case, β_1 would be biased downwards, due to omitted variables that are negatively correlated with abuse/overdoses and positively correlated with PDMP implementation. This would suggest a larger effect of PDMP implementation than is actually the case.

I address these concerns by controlling for the seven other types of laws that may affect opioid abuse, and estimating models that control for pre-treatment trends in PDMP implementation as follows:

(3) $y_{ist} = \alpha + \beta_1(PDMP)_{st} + \theta_1 t_{st} + \theta_2(PDMP_{st} \times t_{st}) + X'_{st}\beta_2 + X'_{ist}\beta_3 + \gamma_s + \delta_t + \varepsilon_{ist}$

(4) $y_{st} = \alpha + \beta_1(PDMP)_{st} + \theta_1 t_{st} + \theta_2(PDMP_{st} \times t_{st}) + X'_{st}\beta_2 + \gamma_s + \delta_t + \varepsilon_{st}$

Where $t_{st} = \begin{cases} year\ relative\ to\ implementation\ if\ state\ implemented\ PDMP \\ 0\ if\ state\ never\ implemented\ PDMP \end{cases}$

Models (3) and (4) are identical to models (1) and (2), respectively, except for the inclusion of the variables $t_{st}$and ($PDMP_{st} \times t_{st}$) in both estimating equations. t_{st} indicates the year relative to implementation for states that have implemented a PDMP. For states that have not done so, this $t_{st}$is set to zero. The inclusion of the interaction term ($PDMP_{st} \times t_{st}$) allows the linear trend in opioid pain reliever abuse to vary before and after PDMP implementation. θ_1

identifies the pre-implementation trend in opioid pain reliever abuse. θ_2 identifies the difference between the pre- and post-implementation trends. In these models, β_1 identifies the trend break at the year of implementation. A statistically significant pre-implementation trend would be evidence of policy endogeneity. By controlling for pre-implementation trends in the model, I am able to identify an arguably unbiased estimate of the policy impact at the year of implementation. A difference in the pre- and post-implementation trends would also suggest that the policy continues to have an effect on outcomes in the years after implementation. This model is essentially a parameterized event study model. Given limitations in sample size, I lack the statistical power to estimate a full event study model. However, the model with pre- and post-implementation trends approximates an event study in testing for policy endogeneity.

Additional threats to identification are cross-border shopping and smuggling. An example of cross-border shopping is when an individual from a state with a PDMP travels to a neighboring state without PDMP to obtain opioid pain relievers. Smuggling refers to drug dealers bringing drugs from states with laxer laws to states where they are harder to obtain. Using the mortality data, I find that only 3.5% of opioid overdose deaths occur outside the decedent's state of residence, which suggests that cross-border shopping may not be a large problem. I also run a robustness check where I drop the states that are known for having high cross-border shopping and smuggling - Florida, Georgia, Kentucky, and Tennessee – and re-estimate models of treatment admissions and overdose deaths.   Results for all models and robustness checks are discussed in the next section.

5. Results

5.1 Self-reported drug use

Table 2 shows summary statistics for the National Survey of Drug Use and Health for years 2004-2011. The proportion of the sample that reports ever using prescription pain relievers nonmedically is 16.2%, and the proportion that reports past year use is 7.5%. The proportion that report ever using Oxycontin nonmedically is 3%, and the proportion for past year use is 1%. Respondents who report using pain relievers nonmedically in the past year report that they used the drugs on 9.4 days, on average, over the past 12 months. They report using pain relievers for 4.9 days per month over the past 12 months. The average reported days of Oxycontin use conditional on past year use are very similar in magnitude to those of pain reliever use. Heroin use is less prevalent than pain reliever and Oxycontin use, while marijuana use is considerable higher.

Table 3 shows results of models of lifetime drug use as a function of PDMPs and other laws. I estimate probit models and report marginal effects. All models control for state and year fixed effects and weight observations using the NSDUH sampling weights. Standard errors are clustered at the state-level. Column (1) is a difference-in-differences model without demographic controls. Demographic controls are added in column (2). Column (3) controls for the year relative to implementation and an interaction between PDMP and the year relative to implementation. These two variables allow for a difference in pre- and post-implementation trends in self-reported drug use. The specification in column (3) is also estimated for Oxycontin, heroin, and marijuana use. I do not find statistically significant effects of PDMPs on lifetime drug use for any of these drugs. Estimates of PDMP impact on lifetime pain reliever and Oxycontin use are 0.334 and 0.117 percentage points, respectively. These have the opposite sign of what we would expect, but the magnitudes of the marginal effects are small relative to the means. I do not find a statistically significant pre-implementation trend, but I do find a statistically significant declining post-implementation trend of 0.07 percentage points per year for Oxycontin. This indicates that reported nonmedical Oxycontin use declines over time after

PDMP implementation. The marginal effects of PDMPs on heroin and marijuana are small in magnitude and not statistically significant. Table 4 shows results of models of past year drug use, and the pattern of results is very similar to that found with lifetime drug use.

Table 5 shows models of past month drug use as function of PDMPs and other state laws. While I do not find statistically significant effects, the marginal effect of PDMPs on Oxycontin use is now -0.027 percentage points, or about 10% of the mean. However, the standard error is large. Tables 6 and 7 show results of OLS models estimating the effect of PDMPs on the number of days the respondent used pain relievers and Oxycontin in the past year and per month in the past year, conditional on use in the past year. The point estimates for both pain relievers and Oxycontin are negative and large relatively to their means, but not statistically significant. This is at best suggestive evidence that PDMPs may have reduced opioid use at the intensive margin.

The estimated effects of the seven other law categories are statistically significant in some models but not others, and the signs are not consistent across models. For example, laws regulating pain clinic appears to have a large and statistically significant positive effect on past year drug use, but a large negative effect on the number of days the respondent use drugs in the past year. One possibility is that there is selection into which states adopt laws regulating pain clinics, with states with higher rates of nonmedical opioid use being likely to do so. Alternatively, collinearity between the law variables may result in the estimated marginal effects of the laws being sensitive to changes in specification.

5.2 Treatment admissions

Table 8 shows summary statistics for the Treatment Episodes Data Set (TEDS) for years 1992-2010. The TEDS data are collapsed to the state-year level and merged to policy and demographic data. The outcome of interest is the number of admissions with a report of opioid abuse, and the rate of admissions per 100,000 of the population aged 10 or older. I use the population aged 10 or older as the relevant population because the TEDS contains information on patients aged 12 and older, and the population estimates are available for 5-year age groups only. The average number of opioid admissions is 2,058, and the average rate of opioid admissions is 49 per 100,000 population.

Table 9 shows results of OLS models of log opioid treatment admissions. Standard errors are clustered at the state level, and observations are weighted by total state population aged 10 or older. Regressions coefficients are reported. Columns (1) shows the difference-in-differences regression of log opioid admissions on PDMP. Column (2) adds demographic and policy variables, including log state population aged 10 or older, shares of total population that are male, Black, and Hispanic, age group shares, the state median household income, average unemployment rate, health insurance coverage, and other laws relevant to opioid abuse. Column (3) additionally controls for year relative to implementation and an interaction of PDMP with year relative to implementation. The coefficient on PDMP in column (2) implies that having a PDMP in place is associated with 21.5%[3] lower opioid treatment admissions. When I allow for pre- and post-implementation trends, the coefficient on year relative to implementation indicates a declining pre-implementation trend of 3.2% per year. This finding is consistent with the story that states with stricter prescribing laws and more enforcement are more likely to adopt PDMPs. However, despite the presence of these trends I still identify a statistically significant reduction in opioid admissions of 13.1% at the time of implementation. The negative coefficient on (PDMP x year relative to implementation) implies that there admissions continue to decline after implementation.

[3] The coefficient of -0.243 in column (2) of table 9 is transformed to the marginal effect of 21.5% by taking $e^{-0.243}$ -1.

As changes in admissions may be driven by either changes in demand for admissions (driven in part by demand for drugs) or changes in treatment supply, I control for a measure of treatment supply. I merge the TEDS data to data from the National Survey of Substance Abuse Treatment Services (N-SSATS) on the number of treatment facilities in state and the number of residential beds available for substance abuse treatment. The N-SSATS data are only available for years 1997-2010. Column (4) of table 9 re-estimates the model from column (3) with data from years 1997-2010 only. Column (5) adds the controls for treatment supply. Comparing columns (4) and (5), we see that the coefficients are very similar at approximately -0.13. The difference between this estimate and the estimate of -0.14 in column (3) appears to be driven by the change in the sample time frame, and not by treatment supply. Because admissions appear not to be driven by treatment supply, and because using the 1997-2010 sample instead of 1992-2010 results in a loss of statistical power, I argue that the results in column (4) are the most reliable. I also estimate alternative models of the rate of admissions, where the outcome variable is log(r/(1-r)), and r is the rate of opioid admissions per 100,000. This functional form recognizes the fact that state-year rates of opioid admissions are grouped data generated by a binary process (i.e. whether an individual is admitted to treatment in a given year). Results for these models are presented in appendix table A.3, and are very similar to the log admissions models discussed above, which control for log state population. Table 10 shows results of models where the outcome is log(p/(1-p)), where p is the share of total treatment admissions that were for opioid abuse. The pattern of results is very similar to the log admissions models in table 9. Column (3) indicates that the presence of a PDMP reduces the odds that a particular admission has a mention of opioids by 16.8%.

Table 11 shows results of models of log opioid, heroin, and marijuana admissions. Column (1) shows the effect of PDMPs on log opioid admissions. This is the same model as column (3) in table 9. Column (2) in table 11 shows results for heroin, and column (3) shows results for marijuana. Heroin is an illicit opioid, and is potentially a substitute for prescription opioids. Marijuana is sometimes used for pain relief, and therefore may also be a potential substitute. I run these models to investigate whether by restricting access to opioids, PDMPs may encourage substitution to other drugs. The coefficients for heroin and marijuana are not statistically significant, and are small in magnitude (-0.03 for heroin and 0.021 for marijuana) compared to the coefficient of -0.140 for opioids. However the standard errors on the both the heroin and marijuana coefficients are large, so the estimates are imprecise. In summary, I argue that I do not find strong evidence of any substitution to heroin or marijuana.

Table 12 shows results of a placebo test of the effect of PDMPs. Column (1) shows my main result for opioids. Column (2) estimates the same model for log alcohol admissions without any mention of opioids. Given that PDMPs do not restrict access to alcohol, we would expect that the policy should not have an effect on alcohol admissions. The point estimate of the effect of PDMPs on alcohol is -0.006 and not statistically significant. This is consistent with what we would expect.

Table 13 shows results of robustness checks of the effect of PDMPs on opioid admissions. Column (1) shows my main result. Column (2) shows the results when I exclude states that are known for high rates of cross-border shopping and smuggling of opioids – Florida, Georgia, Kentucky, and Tennessee. The coefficient is not materially different from the main result, although it is less precisely estimated due to the reduced sample size. Column (3) excludes states that had any form of PDMP prior to their implementation of a modern, third wave PDMP. The coefficient in column (3) is slightly smaller than the main result, but not by much. However it is not statistically significant due to the smaller sample size. Finally, as an alternative to the including pre- and post-implementation trends, I include state-specific linear time trends. This results in a large attenuation of the coefficient to -0.026, and loss of statistical significant. The standard error of the coefficient is also very large, at 0.073. I argue that there is insufficient temporal variation in PDMP implementation to control for state-specific linear time trends, and that controlling and pre- and post- implementation trends addresses concerns about policy endogeneity.

5.3 Overdose deaths

Table 14 shows summary statistics for the Vital Statistics Mortality Data for years 1999-2010. The data are collapsed to the state-year level. The average number of opioid overdose deaths is 205.7, and the average rate of opioid overdose deaths is 4 per 100,000 population. I also look at opioid deaths separately by intent. Unintentional opioid overdose deaths are most common, with a mean of 161. Suicides and deaths of undetermined intent are relatively rare, with a mean of approximately 22 deaths each. From 1999 to 2010, there were 125,873 opioid overdose deaths, of which 98,945 were unintentional, 13,534 were suicides, and 13,394 were deaths of undetermined intent.

Table 15 shows results of models of log opioid overdose deaths. Column (1) shows the difference-in difference estimate of PDMP impact without controlling for demographic characteristics. Controlling for demographics and related policies and results in the coefficient changing from -0.026 to 0.050 in column (3). Results in columns (1) to (3) are not statistically significant. In columns in (4) to (6), I analyze unintentional overdoses, suicides, and deaths of undetermined intent separately. I find that the estimate of PDMP impact is negative for unintentional overdoses (-0.178), but positive for suicides and deaths of undetermined intent (0.129 and 0.380, respectively). The coefficient for undetermined intent deaths is marginally significant. This is surprising, as it is not clear a priori why PDMPs should increase suicides and undetermined intent deaths. However, standard errors on most coefficients in this table are quite large, so we rule negative effects of PDMPs on suicides. Moreover, 79% of all opioid deaths are unintentional, and not suicides or of undetermined intent. Table 16 shows results of models of log opioid and heroin overdose deaths. The coefficient on PDMP for the heroin model is -0.026, and not statistically significant. In Table 17, I robustness checks identical to those run with the TEDS data (shown in table 13), and I find that my results do not change substantially.

6. Discussion

The results indicate that PDMPs reduced opioid treatment admissions. However the impact of PDMPs on self-reported use and opioid overdose deaths is less clear. Point estimates suggest that PDMPs may have reduced pain reliever and Oxycontin at the intensive margin, but the results are not statistically significant. The estimated effect of PDMPs on total opioid overdose deaths is not statistically significant, and the point estimate is small in magnitude and positive. Analyzing deaths separately by intent, I find the point estimates vary by intent, but most results are again not statistically significant, so I cannot say conclusively what the effect of the program was on these separate types of deaths. However, I can say that PDMPs do not appear to have reduced total opioid overdose deaths. Given that both self-reported use and opioid overdose deaths are relatively rare, perhaps it is not surprising that the estimates of PDMP impact are very imprecisely estimated for these outcomes. In the case of self-reported use, under-reporting is highly likely, because many older individuals who are addicted in opioids but who started using them for a legitimate medical purpose may not view their use of pain relievers as “nonmedical” use. Therefore it may be that younger users are more likely to report use. To the extent that these younger users are not doctor shopping but obtaining leftover pain relievers from their parents' medicine cabinets or from friends, PDMPs may have a smaller impact on them than on older users.

Studying impacts of PDMPs on illicit drug use outcomes, I do not find strong evidence that PDMPs induce substitution away from opioids to other drugs. Across datasets I find small negative points estimates of PDMP impacts on heroin use, admissions, and deaths, and small positive estimates for marijuana use and admissions. However in all cases the estimates are not statistically significant. Estimates of the effects of the seven other law categories are not consistent across datasets, so it is also difficult generalize what these may be. Collinearity between the law variables may be driving the large standard errors on the estimates of law impact.

The findings of this paper add to the health economics literature on policies restricting access to addictive substances. Prescription drug abuse is an interesting example of substance abuse because the (usually) legal origin of the drugs makes enforcement difficult. My results suggest that PDMPs are a promising tool for reducing opioid abuse. That I do not find evidence of substitution to illicit drugs is also reassuring. The findings suggest that the few states that do not have a modern PDMP should implement one or upgrade theirs. Reductions in treatment admissions for opioids as a result of having a PDMP can lead to significant cost savings, given that the Affordable Care Act (ACA) will require substance abuse and mental health benefits to be covered at parity with general medical services. However, to understand impacts of PDMPs on other, more rare, health outcomes such as overdose deaths, we may need a longer time frame. It will be possible to do this as more years of data become available. Future research should also address the non-trivial differences in PDMP functioning across states to determine which program features are most effective.

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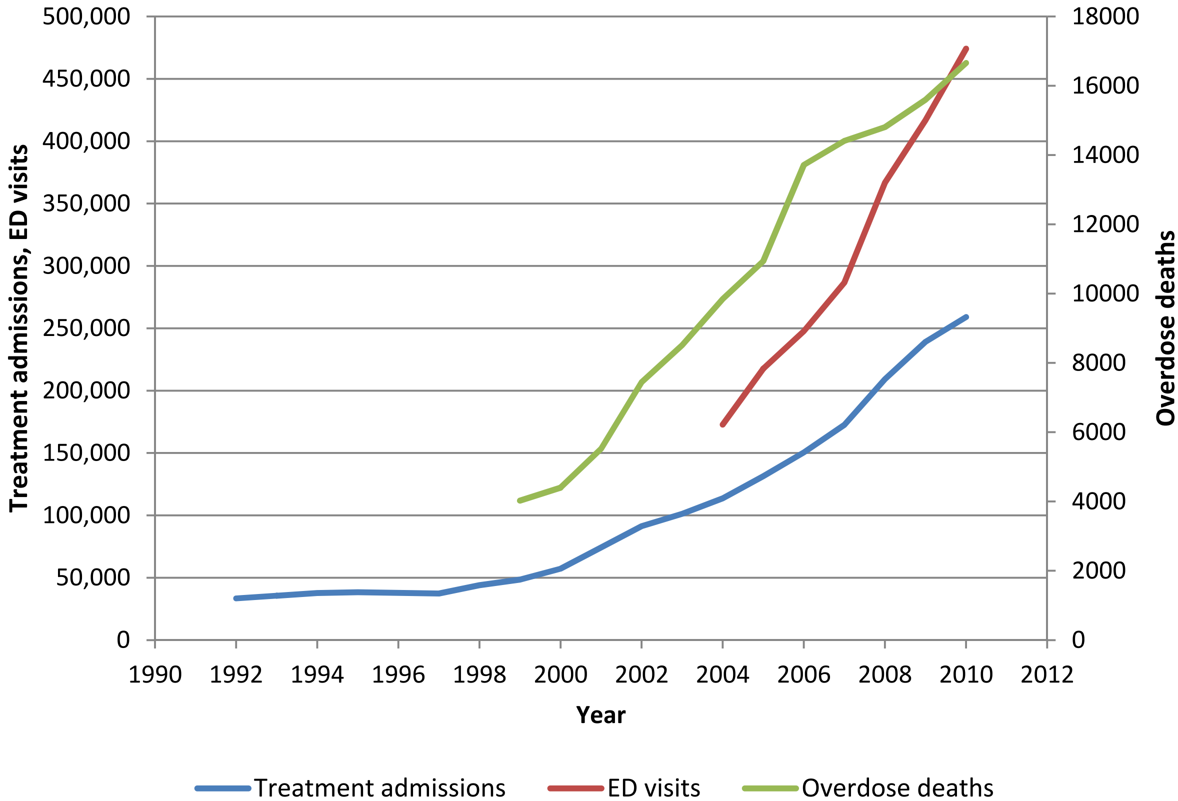
7. Figures and Tables

Figure 1: Trends in opioid overdose deaths, treatment admissions, and emergency department visits



Sources: National Vital Statistics System, 1999-2010; Treatment Episodes Data Set, 1992-2010; Drug Abuse Warning Network (DAWN), 2004-2010

Table 1: Correlation matrix for PDMP and 7 other state law categories

	PDMP	Physical exam law	Tamper-resistant Rx forms law	Pain clinic law	Prescription limits law	ID requirement law	Doctor-shopping law	Immunity from prosecution law
PDMP	1							
Physical exam law	0.1441	1						
Tamper-resistant Rx forms law	0.2015	0.272	1					
Pain clinic law	-0.064	0.126	-0.1413	1				
Prescription limits law	0.0181	0.3076	0.1452	0.1821	1			
ID requirement law	0.0592	0.2215	0.0538	0.351	0.1549	1		
Doctor-shopping law	0.0077	-0.0791	-0.044	0.4483	0.0854	0.3838	1	
Immunity from prosecution law	-0.0559	-0.3433	-0.114	-0.047	-0.2399	-0.1154	-0.0936	1

Notes: Law dates are merged to TEDS 1992-2010 data, which are at the state-year level. Observations are weighted by total state population aged 10 years and older.

Table 2: Self-reported drug use, state laws, and demographics - National Survey on Drug Use and Health 2004 to 2011

	Mean	Count	SD
Self-reported drug use			
Pain relievers - ever used nonmedically	0.162	544800	0.369
Pain relievers - past year nonmedical use	0.075	544800	0.264
Pain relievers - past month nonmedical use	0.030	544800	0.170
Oxycontin - ever used nonmedically	0.030	544800	0.171
Oxycontin - past year nonmedical use	0.011	544800	0.105
Oxycontin - past month nonmedical use	0.003	544800	0.054
Age when first used pain relievers nonmedically	18.661	83400	6.449
No. of days used pain reliever 'nm' in past 12 months	9.403	20800	27.773
No. of days per mo used pain reliever 'nm' in past 12 mos	4.853	10400	5.060
Age when first used oxycontin nonmedically	19.661	15800	6.400
No. of days used oxycontin 'nm' in past 12 months	9.501	3300	29.797
No. of days per month used oxycontin 'nm' in past 12 mos	4.981	1400	5.278
Heroin - ever used	0.013	544800	0.112
Heroin - past year use	0.003	544800	0.053
Heroin - past month use	0.001	544800	0.033
Marijuana - ever used	0.394	544800	0.489
Marijuana - past year use	0.172	544800	0.377
Marijuana - past month use	0.100	544800	0.300
State laws relevant to prescription drug abuse			
PDMP	0.417	544800	0.484
Physical exam law	0.155	544800	0.360
Tamper-resistant Rx forms law	0.147	544800	0.348
Pain clinic law	0.030	544800	0.167
Prescription limits law	0.137	544800	0.340
ID requirement law	0.124	544800	0.329
Doctor-shopping law	0.013	544800	0.115
Immunity from prosecution law	0.018	544800	0.132
State demographics and economic characteristics			
Male	0.483	544800	0.500
Age 12-17 years	0.330	544800	0.470
Age 18-24 years	0.292	544800	0.455
Age 25-34 years	0.137	544800	0.344
Age 35-44 years	0.093	544800	0.290
Age 45-54 years	0.073	544800	0.260
Age 55-64 years	0.037	544800	0.188
Age 65+ years	0.038	544800	0.191
Non-Hispanic White	0.647	544800	0.478
Non-Hispanic Black	0.122	544800	0.328
Hispanic	0.153	544800	0.360
Other race - non-Hispanic	0.078	544800	0.269

Income: <$20K	0.227	544800	0.419
Income: $20-49.9K	0.341	544800	0.474
Income: $50-74.9K	0.171	544800	0.376
Income: >$75K	0.261	544800	0.439
Covered by health insurance	0.795	544800	0.404
Household size	3.579	544800	1.585
Non-metropolitan county	0.215	544800	0.411
Year	2007.515	544800	2.299
State FIPS code	28.600	544800	15.284

Note: The unit of observation is an individual survey respondent.

Table 3: Effect of PDMP on ever using drugs, NSDUH 2004 to 2011

	Any Rx pain relievers			Oxycontin	Heroin	Marijuana
	(1)	(2)	(3)	(4)	(5)	(6)
PDMP	0.00321	0.00297	0.00334	0.00117	-0.00153	0.00326
	(0.00270)	(0.00311)	(0.00300)	(0.00130)	(0.00097)	(0.00480)
Year rel. to implementation of PDMP			0.00039	0.00038	-0.00003	-0.00035
			(0.00129)	(0.00039)	(0.00043)	(0.00221)
PDMP x year rel. to implementation			-0.00072	-0.00071*	0.00003	-0.00019
			(0.00101)	(0.00043)	(0.00039)	(0.00169)
Physical exam law		0.00923***	0.00894***	0.00516	0.00192	0.00500
		(0.00255)	(0.00275)	(0.00527)	(0.00125)	(0.00397)
Tamper-resistant Rx forms law		0.00447	0.00367	-0.00082	-0.00124	-0.00120
		(0.00452)	(0.00517)	(0.00269)	(0.00180)	(0.00644)
Pain clinic law		0.01652***	0.01586***	0.00189**	-0.00024	0.00089
		(0.00243)	(0.00245)	(0.00087)	(0.00094)	(0.00522)
Prescription limits law		0.01368***	0.01399***	0.00154	0.00122	0.00688
		(0.00234)	(0.00241)	(0.00103)	(0.00220)	(0.01046)
ID requirement law		0.01237***	0.01412***	0.00221	0.00057	0.01623**
		(0.00448)	(0.00466)	(0.00165)	(0.00113)	(0.00632)
Doctor-shopping law		0.00810*	0.00847	0.01154**	0.00790***	0.02406
		(0.00429)	(0.00587)	(0.00547)	(0.00293)	(0.01542)
Immunity from prosecution law		0.01381***	0.01444***	0.00210	0.00650**	-0.00460
		(0.00440)	(0.00533)	(0.00236)	(0.00265)	(0.00902)
Year fixed effects	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X
Demographics and related policies		X	X	X	X	X
N	544,800	544,800	544,800	544,800	544,800	544,800

Notes: Dependent variable is lifetime drug use. All models are probit models, and marginal effects are reported. Demographic controls include indicators for whether the respondent is male, non-Hispanic black, Hispanic, other race (non-Hispanic), age 12-17, 18-24, 35-44, 45-54, 55-64, or 65+ years, has family income <$20K, $50-74.9K, and >$75K, lives in non-metropolitan county, is covered by health insurance, and household size. Observations are weighted by NSDUH sampling weights. Standard errors clustered at the state level are reported in parentheses.

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

Table 4: Effect of PDMP on past year drug use, NSDUH 2004 to 2011

	Any Rx pain relievers			Oxycontin	Heroin	Marijuana
	(1)	(2)	(3)	(4)	(5)	(6)
PDMP	0.00267	0.00283	0.00392**	0.00029	-0.00017	0.00118
	(0.00163)	(0.00177)	(0.00172)	(0.00058)	(0.00036)	(0.00272)
Year rel. to implementation of PDMP			-0.00104**	0.00027	-0.00006	0.00210***
			(0.00050)	(0.00017)	(0.00008)	(0.00080)
PDMP x year rel. to implementation			-0.00056	-0.00028	0.00000	0.00031
			(0.00055)	(0.00019)	(0.00016)	(0.00117)
Physical exam law		0.00377***	0.00368***	-0.00052	-0.00014	0.01461**
		(0.00138)	(0.00140)	(0.00050)	(0.00039)	(0.00593)
Tamper-resistant Rx forms law		0.00159	0.00093	0.00061	0.00067	0.00123
		(0.00241)	(0.00245)	(0.00092)	(0.00044)	(0.00394)
Pain clinic law		0.00365**	0.00311*	-0.00097	-0.00216***	0.00046
		(0.00173)	(0.00181)	(0.00059)	(0.00054)	(0.00267)
Prescription limits law		0.00326**	0.00371***	0.00052	-0.00021	-0.00289
		(0.00138)	(0.00122)	(0.00056)	(0.00059)	(0.00246)
ID requirement law		0.00500***	0.00712***	0.00100	0.00022	0.00387
		(0.00134)	(0.00162)	(0.00073)	(0.00063)	(0.00671)
Doctor-shopping law		0.00413*	0.00844***	0.00376***	0.00116	0.02368***
		(0.00250)	(0.00278)	(0.00108)	(0.00109)	(0.00815)
Immunity from prosecution law		0.00736**	0.00574***	0.00099	-0.00124	0.00043
		(0.00362)	(0.00177)	(0.00085)	(0.00085)	(0.00317)
Year fixed effects	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X
Demographics and related policies		X	X	X	X	X
N	544,800	544,800	544,800	544,800	544,800	544,800

Notes: Dependent variable is past year drug use. All models are probit models, and marginal effects are reported. Demographic controls include indicators for whether the respondent is male, non-Hispanic black, Hispanic, other race (non-Hispanic), age 12-17, 18-24, 35-44, 45-54, 55-64, or 65+ years, has family income <$20K, $50-74.9K, and >$75K, lives in non-metropolitan county, is covered by health insurance, and household size. Observations are weighted by NSDUH sampling weights. Standard errors clustered at the state level are reported in parentheses.

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

Table 5: Effect of PDMP on past month drug use, NSDUH 2004 to 2011

	Any Rx pain relievers			Oxycontin	Marijuana
	(1)	(2)	(3)	(6)	(9)
PDMP	-0.00014	0.00025	0.00051	-0.00027	0.00049
	(0.00112)	(0.00125)	(0.00117)	(0.00026)	(0.00241)
Year rel. to implementation of PDMP			-0.00053	0.00003	0.00129*
			(0.00032)	(0.00010)	(0.00070)
PDMP x year rel. to implementation			0.00005	0.00004	-0.00016
			(0.00039)	(0.00010)	(0.00097)
Physical exam law		-0.00116	-0.00108	-0.00089	0.01270***
		(0.00091)	(0.00087)	(0.00055)	(0.00286)
Tamper-resistant Rx forms law		0.00188*	0.00191	0.00010	-0.00084
		(0.00106)	(0.00122)	(0.00038)	(0.00291)
Pain clinic law		0.00005	0.00009	-0.00217***	0.00046
		(0.00146)	(0.00140)	(0.00033)	(0.00214)
Prescription limits law		0.00323***	0.00330***	0.00023	-0.00326
		(0.00114)	(0.00113)	(0.00036)	(0.00229)
ID requirement law		0.00148	0.00164	0.00014	0.00690**
		(0.00112)	(0.00130)	(0.00055)	(0.00340)
Doctor-shopping law		0.00459**	0.00610***	0.00201**	0.01712***
		(0.00182)	(0.00208)	(0.00081)	(0.00459)
Immunity from prosecution law		-0.00115	-0.00198	-0.00081***	0.00332
		(0.00153)	(0.00210)	(0.00030)	(0.00324)
Year fixed effects	X	X	X	X	X
State fixed effects	X	X	X	X	X
Demographics and related policies		X	X	X	X
N	544,800	544,800	544,800	524,200	544,800

Notes: Dependent variable is past month drug use. All models are probit models, and marginal effects are reported. Demographic controls include indicators for whether the respondent is male, non-Hispanic black, Hispanic, other race (non-Hispanic), age 12-17, 18-24, 35-44, 45-54, 55-64, or 65+ years, has family income <$20K, $50-74.9K, and >$75K, lives in non-metropolitan county, is covered by health insurance, and household size. Observations are weighted by NSDUH sampling weights. Standard errors clustered at the state level are reported in parentheses.

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

Table 6: Effect of PDMP on number of days used in past year, NSDUH 2004 to 2011

	Any Rx pain relievers	Oxycontin
	(1)	(2)
PDMP	-1.53595	-3.59188
	(1.67061)	(2.58009)
Year rel. to implementation of PDMP	-0.02277	-1.08579
	(0.39722)	(1.79970)
PDMP x year rel. to implementation	-0.49359	1.27808
	(0.51811)	(1.29170)
Physical exam law	-1.37419	0.92843
	(2.92740)	(4.79964)
Tamper-resistant Rx forms law	6.34079	17.14512*
	(5.77750)	(9.39047)
Pain clinic law	-4.48385**	-16.24341***
	(1.71167)	(3.79088)
Prescription limits law	1.22325	-2.33026
	(1.23666)	(4.01244)
ID requirement law	-0.52876	-14.51962***
	(2.01479)	(4.47042)
Doctor-shopping law	-0.15580	0.78316
	(4.01902)	(8.07926)
Immunity from prosecution law	-5.88176	-26.11836
	(9.14998)	(21.69925)
Year fixed effects	X	X
State fixed effects	X	X
Demographics and related policies	X	X
N	20,800	3,300

Notes: Dependent variable is number of days used drugs nonmedically in past year, conditional on having used the drug in the past year. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include indicators for whether the respondent is male, non-Hispanic black, Hispanic, other race (non-Hispanic), age 12-17, 18-24, 35-44, 45-54, 55-64, or 65+ years, has family income <$20K, $50-74.9K, and >$75K, lives in non-metropolitan county, is covered by health insurance, and household size. Observations are weighted by NSDUH sampling weights. Standard errors clustered at the state level are reported in parentheses.

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

Table 7: Effect of PDMP on number of days used per month in past year, NSDUH 2004 to 2011

	Any Rx pain relievers	Oxycontin
	(3)	(6)
PDMP	-0.29983	-0.08349
	(0.32855)	(0.56700)
Year rel. to implementation of PDMP	-0.28918**	-0.12260
	(0.11675)	(0.14825)
PDMP x year rel. to implementation	0.14809	0.47640*
	(0.12232)	(0.27795)
Physical exam law	-0.72009	0.55565
	(1.01329)	(0.80884)
Tamper-resistant Rx forms law	0.57900	1.59240*
	(0.51307)	(0.91780)
Pain clinic law	0.27191	-7.04498***
	(0.51250)	(0.83346)
Prescription limits law	0.72437**	0.70284
	(0.29552)	(0.59838)
ID requirement law	0.28582	0.35262
	(0.41127)	(1.23951)
Doctor-shopping law	2.60825**	4.04559***
	(1.14394)	(1.42321)
Immunity from prosecution law	-0.70660***	-0.53160
	(0.23849)	(1.06785)
Year fixed effects	X	X
State fixed effects	X	X
Demographics and related policies	X	X
N	10,400	1,400

Notes: Dependent variable is number of days per month used drugs nonmedically in past year, conditional on having used the drug in the past year. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include indicators for whether the respondent is male, non-Hispanic black, Hispanic, other race (non-Hispanic), age 12-17, 18-24, 35-44, 45-54, 55-64, or 65+ years, has family income <$20K, $50-74.9K, and >$75K, lives in non-metropolitan county, is covered by health insurance, and household size. Observations are weighted by NSDUH sampling weights. Standard errors clustered at the state level are reported in parentheses.

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

Table 8: Substance abuse treatment admissions, state laws, and state-level demographics - TEDS 1992 to 2010

	Mean	Count	SD	Min	Max
Substance abuse treatment admissions					
Count of adms with report of opioid abuse	2,058.10	929.00	3,126.87	3.00	36,005.00
Opioid admissions per 100K pop - age 10+ pop	49.58	929.00	65.45	0.60	537.09
Share of total admissions that are for opioids	0.06	929.00	0.07	0.00	0.44
Count of adms with report of alcohol abuse	24,275.81	929.00	32,482.70	508.00	236,197.00
Count of adms with report of marijuana abuse	12,639.74	929.00	16,076.23	211.00	126,018.00
Count of adms with report of heroin abuse	6,121.04	929.00	13,450.08	1.00	81,106.00
Count of adms with report of cocaine abuse	11,386.61	929.00	19,864.22	104.00	151,411.00
State laws relevant to prescription drug abuse					
PDMP	0.20	929.00	0.39	0.00	1.00
Physical exam law	0.69	929.00	0.46	0.00	1.00
Tamper-resistant Rx forms law	0.31	929.00	0.46	0.00	1.00
Pain clinic law	0.04	929.00	0.19	0.00	1.00
Prescription limits law	0.57	929.00	0.49	0.00	1.00
ID requirement law	0.35	929.00	0.47	0.00	1.00
Doctor shopping law	0.31	929.00	0.46	0.00	1.00
Immunity from prosecution law	0.03	929.00	0.17	0.00	1.00
State demographics and economic characteristics					
Total pop age 10+	4,887,854.83	929.00	5,378,342.45	393,428.00	32,298,784.00
Male	0.49	929.00	0.01	0.47	0.53
Percent Black	11.10	929.00	10.89	0.28	65.16
Percent other race	5.90	929.00	10.33	0.55	73.26
Percent Hispanic	8.16	929.00	9.05	0.44	46.44
Percent aged 10-14 of 10+ pop	8.32	929.00	0.85	5.15	13.02
Percent aged 15-24 of 10+ pop	16.53	929.00	1.42	13.58	24.18
Percent aged 25-34 of 10+ pop	16.19	929.00	2.07	12.01	23.81
Percent aged 35-44 of 10+ pop	17.55	929.00	1.75	12.72	24.46
Percent aged 45-54 of 10+ pop	15.63	929.00	1.65	10.56	19.31
Percent aged 55-64 of 10+ pop	11.08	929.00	1.78	6.79	16.31
Percent aged 65+ of 10+ pop	14.70	929.00	2.02	5.25	21.23
State median household income	50,715.42	929.00	7,795.75	30,864.00	73,598.00
Average state unemployment rate	5.37	929.00	1.80	2.30	13.70
Percent health insurance coverage	86.42	929.00	3.98	74.40	95.70
No. of treatment facilities	263.39	692.00	284.20	20.00	1,820.00
No. of residential beds	2,178.55	692.00	3,257.53	89.00	20,171.00
Year	2,001.06	929.00	5.44	1,992.00	2,010.00
State FIPS code	29.33	929.00	15.45	1.00	56.00

Note: The unit of observation is a state-year. State-level policy, economic and demographic data are merged to the TEDS by state and year.

Table 9: Effect of PDMP on log opioid admissions, TEDS 1992-2010

	1992-2010			1997-2010	
				No controls for treatment supply	Controls for treatment supply
	(1)	(2)	(3)	(4)	(5)
PDMP	-0.220*	-0.243***	-0.140**	-0.130*	-0.125*
	(0.112)	(0.058)	(0.066)	(0.074)	(0.074)
Year rel. to implementation of PDMP			-0.033***	-0.005	-0.012
			(0.011)	(0.018)	(0.019)
PDMP x year rel. to implementation			-0.037	-0.051*	-0.052*
			(0.026)	(0.027)	(0.029)
Physical exam law		-0.112	-0.102	-0.247	-0.256
		(0.123)	(0.120)	(0.158)	(0.157)
Tamper-resistant Rx forms law		0.059	0.077	0.011	0.005
		(0.141)	(0.141)	(0.185)	(0.184)
Pain clinic law		-0.066	-0.104	-0.196	-0.287
		(0.228)	(0.252)	(0.388)	(0.397)
Prescription limits law		0.002	-0.047	0.100	0.098
		(0.116)	(0.128)	(0.131)	(0.139)
ID requirement law		-0.083	-0.004	-0.025	-0.042
		(0.154)	(0.151)	(0.141)	(0.139)
Doctor shopping law		0.265	0.328	-0.776***	-0.735***
		(0.208)	(0.216)	(0.243)	(0.254)
Immunity from prosecution law		-0.288*	-0.419**	-0.291**	-0.346**
		(0.147)	(0.161)	(0.143)	(0.137)
Year fixed effects	X	X	X	X	X
State fixed effects	X	X	X	X	X
Demographic controls		X	X	X	X
Treatment supply controls					X
N	929	929	929	692	692

Notes: Dependent variable is the natural log of opioid admissions. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population aged 10 and older, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 10-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Controls for treatment supply include number of substance abuse treatment facilities in state and number of residential beds available for substance abuse treatment. Observations are weighted by the state population aged 10 and older. Standard errors clustered at the state level are reported in parentheses.

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

Table 10: Effect of PDMP on share of total admissions that are for opioids, TEDS 1992-2010

	1992-2010			1997-2010	
				No controls for treatment supply	Controls for treatment supply
	(1)	(2)	(3)	(4)	(5)
PDMP	-0.249**	-0.235***	-0.184**	-0.130*	-0.123
	(0.101)	(0.060)	(0.073)	(0.075)	(0.075)
Year rel. to implementation of PDMP			-0.018**	-0.003	-0.013
			(0.008)	(0.014)	(0.014)
PDMP x year rel. to implementation			-0.017	-0.028	-0.030
			(0.021)	(0.024)	(0.026)
Physical exam law		-0.150*	-0.143*	-0.176	-0.188*
		(0.080)	(0.080)	(0.110)	(0.105)
Tamper-resistant Rx forms law		0.164*	0.174*	0.094	0.086
		(0.094)	(0.095)	(0.113)	(0.105)
Pain clinic law		-0.100	-0.118	-0.371**	-0.496***
		(0.237)	(0.253)	(0.139)	(0.159)
Prescription limits law		0.048	0.023	0.099	0.097*
		(0.057)	(0.050)	(0.061)	(0.054)
ID requirement law		0.074	0.112	0.138	0.116
		(0.125)	(0.119)	(0.115)	(0.111)
Doctor shopping law		0.369**	0.398**	-0.112	-0.055
		(0.176)	(0.186)	(0.157)	(0.172)
Immunity from prosecution law		-0.130	-0.197	0.001	-0.074
		(0.253)	(0.227)	(0.135)	(0.142)
Year fixed effects	X	X	X	X	X
State fixed effects	X	X	X	X	X
Demographic controls		X	X	X	X
Treatment supply controls					X
N	929	929	929	692	692

Notes: Dependent variable is log(p/(1-p)), where p=share of total admissions that are for opioids. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population aged 10 and older, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 10-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Controls for treatment supply include number of substance abuse treatment facilities in state and number of residential beds available for substance abuse treatment. Observations are weighted by the state population aged 10 and older. Standard errors clustered at the state level are reported in parentheses.

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

Table 11: Effect of PDMP on log opioid, heroin, and marijuana admissions, TEDS 1992-2010

	Opioids	Heroin	Marijuana
	(1)	(2)	(3)
PDMP	-0.140**	-0.030	0.021
	(0.066)	(0.091)	(0.055)
Year rel. to implementation of PDMP	-0.033***	-0.018	-0.007
	(0.011)	(0.015)	(0.012)
PDMP x year rel. to implementation	-0.037	0.021	-0.020
	(0.026)	(0.038)	(0.020)
Physical exam law	-0.102	-0.204	0.039
	(0.120)	(0.229)	(0.109)
Tamper-resistant Rx forms law	0.077	-0.184	-0.061
	(0.141)	(0.190)	(0.118)
Pain clinic law	-0.104	-0.107	-0.053
	(0.252)	(0.219)	(0.090)
Prescription limits law	-0.047	-0.156	-0.050
	(0.128)	(0.157)	(0.129)
ID requirement law	-0.004	-0.001	-0.260
	(0.151)	(0.137)	(0.160)
Doctor shopping law	0.328	0.284	0.054
	(0.216)	(0.462)	(0.183)
Immunity from prosecution law	-0.419**	-0.164	-0.279
	(0.161)	(0.331)	(0.192)
Year fixed effects	X	X	X
State fixed effects	X	X	X
Demographic controls	X	X	X
N	929	929	929

Notes: Dependent variable is the natural log of admissions. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population aged 10 and older, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 10-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Observations are weighted by the state population aged 10 and older. Standard errors clustered at the state level are reported in parentheses.

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

Table 12: Placebo test - effect of PDMP on log alcohol admissions without mention of opioids, TEDS 1992-2010

	Opioids	Alcohol (non-opioids)
	(1)	(2)
PDMP	-0.140**	-0.006
	(0.066)	(0.058)
Year rel. to implementation of PDMP	-0.033***	-0.008
	(0.011)	(0.010)
PDMP x year rel. to implementation	-0.037	-0.015
	(0.026)	(0.017)
Physical exam law	-0.102	0.009
	(0.120)	(0.124)
Tamper-resistant Rx forms law	0.077	-0.093
	(0.141)	(0.107)
Pain clinic law	-0.104	0.087
	(0.252)	(0.092)
Prescription limits law	-0.047	-0.086
	(0.128)	(0.127)
ID requirement law	-0.004	-0.165
	(0.151)	(0.136)
Doctor shopping law	0.328	-0.148
	(0.216)	(0.160)
Immunity from prosecution law	-0.419**	-0.242
	(0.161)	(0.269)
Year fixed effects	X	X
State fixed effects	X	X
Demographic controls	X	X
N	929	929

Notes: Dependent variable is the natural log of admissions. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population aged 10 and older, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 10-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Observations are weighted by the state population aged 10 and older. Standard errors clustered at the state level are reported in parentheses.

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

Table 13: Robustness checks: Effect of PDMP on log opioid admissions, TEDS 1992-2010

	(1)	(2)	(3)	(4)
PDMP	-0.140**	-0.120*	-0.116	-0.026
	(0.066)	(0.071)	(0.097)	(0.073)
Year rel. to implementation of PDMP	-0.033***	-0.025**	-0.044**	
	(0.011)	(0.012)	(0.018)	
PDMP x year rel. to implementation	-0.037	-0.045	-0.025	
	(0.026)	(0.028)	(0.037)	
Physical exam law	-0.102	-0.094	-0.075	0.016
	(0.120)	(0.122)	(0.167)	(0.193)
Tamper-resistant Rx forms law	0.077	0.012	-0.038	0.103
	(0.141)	(0.188)	(0.173)	(0.178)
Pain clinic law	-0.104	-0.146	0.373**	-0.149
	(0.252)	(0.271)	(0.168)	(0.243)
Prescription limits law	-0.047	-0.037	0.044	0.210
	(0.128)	(0.140)	(0.120)	(0.220)
ID requirement law	-0.004	-0.020	0.075	-0.035
	(0.151)	(0.162)	(0.276)	(0.197)
Doctor shopping law	0.328	0.428*	0.776	-0.295
	(0.216)	(0.237)	(4.993)	(0.228)
Immunity from prosecution law	-0.419**	-0.282*	-0.510**	-0.061
	(0.161)	(0.164)	(0.204)	(0.236)
Year fixed effects	X	X	X	X
State fixed effects	X	X	X	X
Demographic controls	X	X	X	X
Exclude high x-border shopping states		X		
Exclude early implementers			X	
State-specific linear trends				X
N	929	862	651	929

Notes: Dependent variable is the natural log of admissions. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population aged 10 and older, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 10-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Controls for treatment supply include number of substance abuse treatment facilities in state and number of residential beds available for substance abuse treatment. Observations are weighted by the state population aged 10 and older. Standard errors clustered at the state level are reported in parentheses.

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

Table 14: Overdose deaths, state laws, and state-level demographics - Vital Statistics Mortality Data 1999 to 2010

	Mean	Count	SD	Min	Max
Overdose deaths					
Total opioid overdose deaths	205.68	612.00	251.51	1.00	1669.00
Count of opioid overdose deaths - unintentional	161.68	612.00	216.43	0.00	1463.00
Count of opioid overdose deaths - suicide	22.11	612.00	28.37	0.00	197.00
Count of opioid overdose deaths - undetermined intent	21.89	612.00	39.71	0.00	328.00
Total opioid deaths per 100K pop	4.01	612.00	3.09	0.14	23.84
Total heroin deaths per 100K pop	0.67	612.00	0.76	0.00	4.38
State laws relevant to prescription drug abuse					
PDMP	0.29	612.00	0.45	0.00	1.00
Physical exam law	0.75	612.00	0.43	0.00	1.00
Tamper-resistant Rx forms law	0.34	612.00	0.47	0.00	1.00
Pain clinic law	0.04	612.00	0.20	0.00	1.00
Prescription limits law	0.61	612.00	0.49	0.00	1.00
ID requirement law	0.37	612.00	0.48	0.00	1.00
Doctor shopping law	0.31	612.00	0.46	0.00	1.00
Immunity from prosecution law	0.03	612.00	0.18	0.00	1.00
Total state population	5771296.39	612.00	6429683.50	491780.00	37338198.00
State demographics and economic characteristics					
Male	0.49	612.00	0.01	0.47	0.52
Percent Black	11.72	612.00	11.53	0.35	62.09
Percent other race	6.30	612.00	10.26	0.66	73.20
Percent Hispanic	9.11	612.00	9.31	0.57	46.44
Percent of total pop aged 0-14	20.37	612.00	1.75	13.91	26.79
Percent of total pop aged 15-24	14.39	612.00	1.08	11.78	19.82
Percent of total pop aged 25-34	13.23	612.00	1.28	10.71	20.78
Percent of total pop aged 35-44	14.56	612.00	1.33	11.13	18.71
Percent of total pop aged 45-54	14.38	612.00	1.00	10.42	17.13
Percent of total pop aged 55-64	10.37	612.00	1.44	6.34	14.55
Percent of total pop aged 65+	12.71	612.00	1.76	5.48	17.76
State median household income	51745.52	612.00	7788.25	35582.00	73598.00
Average state unemployment rate	5.40	612.00	1.96	2.30	13.70
Percent health insurance coverage	86.71	612.00	3.92	74.50	95.70
Year	2004.50	612.00	3.46	1999.00	2010.00
FIPS State of death	28.96	612.00	15.69	1.00	56.00

Note: The unit of observation is a state-year. State-level policy, economic and demographic data are merged to mortality data by state and year.

Table 15: Effect of PDMP on log opioid overdose deaths, Vital Statistics Mortality 1999 to 2010

	Total opioid deaths			Unintentional	Suicides	Undetermined
	(1)	(2)	(3)	(4)	(5)	(6)
PDMP	-0.026	0.070	0.050	-0.178	0.129	0.380*
	(0.147)	(0.106)	(0.096)	(0.190)	(0.101)	(0.208)
Year rel. to implementation			-0.014	0.031	-0.016	0.013
			(0.033)	(0.061)	(0.029)	(0.053)
PDMP x year rel. to implementation			0.040	0.047	0.052*	0.071
			(0.025)	(0.040)	(0.028)	(0.069)
Physical exam law		0.247	0.272	0.548*	0.257	-0.007
		(0.183)	(0.198)	(0.298)	(0.401)	(0.299)
Tamper-resistant Rx forms law		0.031	0.055	0.083	-0.126	0.165
		(0.098)	(0.091)	(0.191)	(0.124)	(0.190)
Pain clinic law		0.350***	0.354***	0.512**	0.168	0.106
		(0.125)	(0.125)	(0.231)	(0.167)	(0.367)
Prescription limits law		0.115	0.092	-0.064	-0.173	0.260
		(0.258)	(0.259)	(0.306)	(0.151)	(0.306)
ID requirement law		0.051	-0.046	0.049	-0.320*	-0.230
		(0.100)	(0.132)	(0.157)	(0.169)	(0.397)
Doctor shopping law		0.306	0.267	0.514*	-1.048***	-0.955**
		(0.186)	(0.170)	(0.296)	(0.216)	(0.399)
Immunity from prosecution law		0.265	0.227	1.376	0.067	0.875*
		(0.328)	(0.370)	(0.890)	(0.248)	(0.518)
Year fixed effects	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X
Demographic controls		X	X	X	X	X
N	612	612	612	612	612	612

Notes: Dependent variable is the natural log of overdose deaths. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 0-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Observations are weighted by the total state population. Standard errors clustered at the state level are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table 16: Effect of PDMP on log opioid and heroin overdose deaths, Vital Statistics Mortality 1999 to 2010

	Opioids	Heroin
	(1)	(2)
PDMP	0.050	-0.026
	(0.096)	(0.155)
Year rel. to implementation	-0.014	-0.032
	(0.033)	(0.089)
PDMP x year rel. to implementation	0.040	0.061
	(0.025)	(0.047)
Physical exam law	0.272	0.059
	(0.198)	(0.379)
Tamper-resistant Rx forms law	0.055	-0.516**
	(0.091)	(0.226)
Pain clinic law	0.354***	0.389
	(0.125)	(0.255)
Prescription limits law	0.092	0.292
	(0.259)	(0.585)
ID requirement law	-0.046	-0.560**
	(0.132)	(0.258)
Doctor shopping law	0.267	0.741*
	(0.170)	(0.416)
Immunity from prosecution law	0.227	0.220
	(0.370)	(0.468)
Year fixed effects	X	X
State fixed effects	X	X
Demographic controls	X	X
N	612	612

Notes: Dependent variable is the natural log of overdose deaths. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 0-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Observations are weighted by the total state population. Standard errors clustered at the state level are reported in parentheses.

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

Table 17: Robustness checks: Effect of PDMP on log opioid overdose deaths, Vital Statistics Mortality 1999 to 2010

	(1)	(2)	(3)	(4)
PDMP	0.050	0.036	0.010	0.042
	(0.096)	(0.109)	(0.096)	(0.103)
Year rel. to implementation	-0.014	-0.010	-0.052	
	(0.033)	(0.033)	(0.034)	
PDMP x year rel. to implementation	0.040	0.040	-0.017	
	(0.025)	(0.031)	(0.018)	
Physical exam law	0.272	0.270	0.132	0.299
	(0.198)	(0.195)	(0.181)	(0.272)
Tamper-resistant Rx forms law	0.055	0.151	0.102	0.008
	(0.091)	(0.094)	(0.111)	(0.113)
Pain clinic law	0.354***	0.392***	-9.315**	-0.080
	(0.125)	(0.143)	(3.500)	(0.114)
Prescription limits law	0.092	0.079	0.124	-0.005
	(0.259)	(0.245)	(0.154)	(0.119)
ID requirement law	-0.046	-0.060	0.165*	-0.062
	(0.132)	(0.169)	(0.095)	(0.133)
Doctor shopping law	0.267	0.348*	7.060**	0.399**
	(0.170)	(0.201)	(3.329)	(0.170)
Immunity from prosecution law	0.227	0.194	0.517	0.063
	(0.370)	(0.375)	(0.541)	(0.500)
Year fixed effects	X	X	X	X
State fixed effects	X	X	X	X
Demographic controls	X	X	X	X
Exclude high x-border shopping states		X		
Exclude early implementers			X	
State-specific linear trends				X
N	612	564	432	612

Notes: Dependent variable is the natural log of overdose deaths. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include log state population, median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 0-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Observations are weighted by the total state population. Standard errors clustered at the state level are reported in parentheses.

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

Appendix

Table A.1: Operational start dates of third wave of PDMP implementation

State	Year	State	Year
Idaho	1997*	Illinois	2008*
Rhode Island	1997*	Texas	2008*
Nevada	1997	South Carolina	2008
Utah	1997	Louisiana	2008
Kentucky	1999	Connecticut	2008
Michigan	2003*	Arizona	2008
West Virginia	2003*	Iowa	2009
Maine	2004	Vermont	2009
Wyoming	2004	Nebraska	2009
California	2005*	Minnesota	2010
New York	2005*	Massachusetts	2011*
Indiana	2005*	Kansas	2011
New Mexico	2005*	Oregon	2011
Mississippi	2005	South Dakota	2011
Oklahoma	2006*	Alaska	2011
Virginia	2006*	Florida	2011
Ohio	2006	New Jersey	2011
Alabama	2006	Washington	2011
Tennessee	2006	Delaware	2012
North Dakota	2007	Montana	2012
Colorado	2007	Arkansas	2012
North Carolina	2007	Georgia	2012
Hawaii	2008*	Wisconsin	2013

Notes: Operational start date is defined as the date the PDMP started collecting data. As of July 2013, four states (Missouri, Maryland, New Hampshire, Philadelphia) and D.C. did not have operational, modern PDMPs. Maryland and New Hampshire have enacted PDMP legislation but their programs are not yet operational. Philadelphia has a older era PDMP in place, but it does not make reports available to doctors and pharmacists. States marked with a '*' had older programs in place prior to the third wave of PDMP implementation. These older programs included paper programs, electronic programs that tracked only Schedule II drugs and did not make data available to doctors, and pilot programs that were in effect for a short time period and in only part of the state.

Table A.2: Definitions of specific causes of mortality: ICD-10 codes

Cause of death	Underlying cause of death codes	Record axis condition codes
Unintentional opioid overdose	X40-44	T40.2, T40.3, T40.4
Suicide - opioid overdose	X60-64	T40.2, T40.3, T40.4
Opioid overdose of undetermined intent	Y10-14	T40.2, T40.3, T40.4
Opioid overdose (unintentional, suicide or undetermined intent)	X40-44, X60-64, Y10-14	T40.2, T40.3, T40.4
Heroin overdose (unintentional, suicide or undetermined intent)	X40-44, X60-64, Y10-14	T40.1

Note: Mortality data is from the Vital Statistics Mortality datafiles. From 1999 onwards, cause of death is classified using the 10th revision of the International Classification of Diseases (ICD-10).

Table A.3: Effect of PDMP on opioid admissions rate, TEDS 1992-2010

	1992-2010			1997-2010	
				No controls for treatment supply	Controls for treatment supply
	(1)	(2)	(3)	(4)	(5)
PDMP	-0.213*	-0.243***	-0.141**	-0.133*	-0.128*
	(0.120)	(0.058)	(0.066)	(0.075)	(0.074)
Year rel. to implementation of PDMP			-0.033***	-0.007	-0.014
			(0.011)	(0.019)	(0.020)
PDMP x year rel. to implementation			-0.037	-0.050*	-0.051*
			(0.026)	(0.028)	(0.029)
Physical exam law		-0.112	-0.102	-0.237	-0.245
		(0.124)	(0.122)	(0.159)	(0.159)
Tamper-resistant Rx forms law		0.058	0.075	0.008	0.002
		(0.139)	(0.138)	(0.187)	(0.186)
Pain clinic law		-0.068	-0.108	-0.173	-0.260
		(0.230)	(0.256)	(0.383)	(0.389)
Prescription limits law		0.004	-0.045	0.083	0.080
		(0.116)	(0.129)	(0.125)	(0.133)
ID requirement law		-0.086	-0.008	-0.022	-0.038
		(0.154)	(0.151)	(0.144)	(0.142)
Doctor shopping law		0.274	0.341*	-0.792***	-0.753***
		(0.189)	(0.202)	(0.247)	(0.258)
Immunity from prosecution law		-0.283*	-0.410**	-0.311*	-0.368**
		(0.160)	(0.176)	(0.157)	(0.153)
Year fixed effects	X	X	X	X	X
State fixed effects	X	X	X	X	X
Demographic controls		X	X	X	X
Treatment supply controls					X
N	929	929	929	692	692

Notes: Dependent variable is log(r/(1-r)), where r=number of opioid admissions per 100,000 population aged 10 years and older. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 10-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Controls for treatment supply include number of substance abuse treatment facilities in state and number of residential beds available for substance abuse treatment. Observations are weighted by the state population aged 10 and older. Standard errors clustered at the state level are reported in parentheses.

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

Table A.4: Effect of PDMP on opioid overdose death rate, Vital Statistics Mortality 1999 to 2010

	Total opioid deaths			Unintentional	Suicides	Undetermined
	(1)	(2)	(3)	(4)	(5)	(6)
PDMP	-0.015	0.083	0.064	-0.161	0.150	0.395*
	(0.149)	(0.105)	(0.094)	(0.187)	(0.100)	(0.207)
Year rel. to implementation			-0.008	0.037	-0.008	0.018
			(0.034)	(0.061)	(0.033)	(0.053)
PDMP x year rel. implementation			0.034	0.040	0.044	0.065
			(0.026)	(0.041)	(0.029)	(0.068)
Physical exam law		0.200	0.217	0.479	0.176	-0.064
		(0.180)	(0.191)	(0.293)	(0.380)	(0.296)
Tamper-resistant Rx forms law		0.050	0.072	0.104	-0.101	0.182
		(0.094)	(0.088)	(0.190)	(0.126)	(0.190)
Pain clinic law		0.260**	0.258**	0.394*	0.028	0.009
		(0.126)	(0.122)	(0.223)	(0.154)	(0.322)
Prescription limits law		0.179	0.168	0.029	-0.062	0.337
		(0.275)	(0.279)	(0.313)	(0.172)	(0.329)
ID requirement law		0.061	-0.021	0.080	-0.284*	-0.205
		(0.098)	(0.129)	(0.152)	(0.162)	(0.391)
Doctor shopping law		0.309	0.276	0.524*	-1.036***	-0.947**
		(0.188)	(0.177)	(0.301)	(0.224)	(0.402)
Immunity from prosecution law		0.278	0.255	1.410	0.107	0.903*
		(0.312)	(0.347)	(0.890)	(0.224)	(0.504)
Year fixed effects	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X
Demographic controls		X	X	X	X	X
N	612	612	612	612	612	612

Notes: Dependent variable is log(r/(1-r)), where r=number of overdose deaths per 100,000 population. All regressions estimated with least squares, and regression coefficients are reported. Demographic controls include median HH income, average state unemployment rates, percent of state with health insurance coverage, and shares of the state population who are: male, black, Hispanic, other race, and aged 0-14, 15-24, 35-44, 45-54, 55-64, and 65+ years old. Observations are weighted by the total state population. Standard errors clustered at the state level are reported in parentheses.

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