Addictive Behaviors 69 (2017) 65–77

Contents lists available at ScienceDirect

Addictive Behaviors

journal homepage: www.elsevier.com/locate/addictbeh

Prescription drug monitoring programs, nonmedical use of prescription drugs, and heroin use: Evidence from the National Survey of Drug Use and Health

Mir M. Ali [a,*], William N. Dowd [b], Timothy Classen [c], Ryan Mutter [a], Scott P. Novak [d]

[a] Center for Behavioral Health Statistics & Quality, Substance Abuse & Mental Health Services Administration, 5600 Fishers Lane, Rockville, MD 20852, United States
[b] Behavioral Health Economics, RTI International, United States
[c] Department of Economics, Loyola University Chicago, United States
[d] Behavioral Health Epidemiology, RTI International, United States

HIGHLIGHTS

- First paper to examine the role of prescription drug monitoring program (PDMP) on individual level opioid related outcomes.
- Significant association between PDMP implementation and reduction in 'doctor shopping' behavior.
- No significant associations between PDMP implementation or its associated features on heroin initiation.
- No significant associations between PDMP implementation on nonmedical use/initiation/abuse of opioids.

ARTICLE INFO

Article history:
Received 12 October 2016
Received in revised form 20 December 2016
Accepted 4 January 2017
Available online 6 January 2017

Keywords:
Prescription drug monitoring program
Opioid
Heroin
Source of provider

ABSTRACT

In the United States, nonmedical prescription opioid use is a major public health concern. Various policy initiatives have been undertaken to tackle this crisis, including state prescription drug monitoring programs (PDMPs). This study uses the 2004–2014 National Survey of Drug Use and Health (NSDUH) and exploits state-level variation in the timing of PDMP implementation and PDMP characteristics to investigate whether PDMPs are associated with a reduction in prescription opioid misuse or whether they have the unintended consequence of increasing heroin use. In addition, the study examines the impact of PDMPs on the availability of opioids from various sources. The study finds no effect of PDMP status on various measures of nonmedical prescription opioid use (abuse, dependence, and initiation), but finds evidence of a reduction in the number of days of opioid misuse in the past year. The study also finds that implementation of PDMP was not associated with an increase in heroin use or initiation, but was associated with an increase in number of days of heroin use in the past year. Findings also suggest that PDMPs were associated with a significant decline in doctor shopping among individuals without increasing reliance on illegal sources (e.g., drug dealers, stealing, etc.) or social sources (friends or relatives) as a means of obtaining opioids. The President's FY2017 budget proposed the allocation of $1.1 billion in an effort to reduce prescription drug misuse, and highlighted the use of PDMPs as a policy tool. This study documents evidence that PDMPs might be having measurable impact.

Published by Elsevier Ltd.

1. Introduction

Nonmedical use of prescription pain relievers (NMPR), particularly opioid analgesics, is a major public health concern in the United States as evidenced by increasing numbers of emergency department visits (Cai, Crane, Poneleit, & Paulozzi, 2010), treatment admissions (Ling, Mooney, & Hillhouse, 2011), and fatal overdoses (Centers for Disease Control and Prevention, 2016). Opioids accounted for 61% of all drug-related overdose deaths in 2014 (Rudd, Aleshire, Zibbell, & Gladden, 2016)—a rate that has nearly quadrupled since 2000 (Compton, Jones, & Baldwin, 2016). In addition, opioid-related hospitalizations increased 150% between 1993 and 2012 (Owens, Barrett, Weiss, Washington, & Kronick, 2014).

* Corresponding author.
E-mail address: mir.ali@samhsa.hhs.gov (M.M. Ali).

http://dx.doi.org/10.1016/j.addbeh.2017.01.011
0306-4603/Published by Elsevier Ltd.

In response to the threat posed by NMPR use, federal and state agencies have implemented several different types of regulations, policies, and programs aimed at reducing opioid misuse and associated outcomes. These initiatives range from educational efforts targeted at health service providers and the general public about appropriate use, law enforcement engagement aimed at reducing inappropriate prescribing (i.e. eliminating "pill mills," Chang et al., 2016), naloxone access laws and programs, and developing abuse-deterrent opioids. Another such policy initiative is the implementation of or strengthening of prescription drug monitoring programs (PDMPs) at the state level to track prescriptions of controlled substances. PDMPs are state-run electronic databases designed to track prescribing and dispensing of prescription drugs classified as controlled substances. These databases are intended not only to reduce over-prescribing of pain medications by doctors but also to identify individuals at high risk for opioid use disorder, such as individuals with opioid prescriptions from multiple providers. The types of drugs that are tracked by the PDMPs vary by state, but they typically include Schedule II and III opioids, which are those with a high potential for abuse available only by prescription. The PDMPs are accessible to physicians, pharmacists, other health care providers, and law enforcement agencies.

The U.S. Department of Health and Human Services (DHHS) considers PDMPs to be among the most important policy mechanisms for reducing prescription drug abuse (Department of Health and Human Services & Assistant Secretary for Planning and Evaluation, 2015). Recent research has shown that PDMPs are effective in reducing the number of prescriptions written for opioids (Bao et al., 2016). Data have also shown that opioid-related mortality is lower in states with a PDMP than in states without a PDMP (Patrick, Fry, Jones, & Buntin, 2016). To date, no studies have examined the impact of PDMPs on opioid-related outcomes among a nationally representative population. For example, Bao et al. (2016) analyzed data from office-based physicians' visits only and found a reduction in prescriptions issued for Schedule II opioids, and Meara et al. (2016) studied disabled Medicare beneficiaries and found little impact of PDMPs on opioid prescribing. Chang et al. (2016) studied the impact of PDMPs on opioid prescribing in Florida and Georgia, and found a reduction in prescribing patterns only among high-volume prescribers. These apparently conflicting findings from the literature suggest that PDMPs might not have a uniform impact on prescribers and patients and across substances. In addition, no studies to date have examined the impact of PDMPs on initiation, use, and addiction in the nonmedical use of prescription opiate painkillers among a nationally representative population.

In this study, we use state-level variation in the dates of PDMP implementation to investigate associations between PDMP status and NMPR use and associated outcomes on a nationally representative sample of adults in the United States. In addition, associations with PDMP characteristics are explored. Although PDMPs are designed as a policy tool targeted toward providers, examination of patient-level outcomes is important because a reduction in the rates of individual-level opiate misuse is the main policy goal. In addition, some are concerned that an unintended consequence of the policies and practices implemented to curb opioid misuse might be an increase in the rates of heroin use (Compton et al., 2016) given that heroin use is 19 times higher among those who report prior nonmedical use of prescription drugs than among those who do not (Muhuri, Gfroerer, & Davies, 2013). To our knowledge, no studies to date have examined the impact of PDMPs on heroin use using a nationally representative population data. Many opioid and heroin misuse related policy measures have been put in place and even though it is beyond the scope of this paper to examine all of them simultaneously, this study makes the important first step in testing for an association between PDMP and opioid and heroin related outcomes at the individual level.

2. Materials and methods

2.1. Design

Respondent data for this analysis were drawn from the National Survey of Drug Use and Health (NSDUH) conducted by the Substance Abuse and Mental Health Services Administration (SAMHSA). NSDUH is an annual nationwide survey of the civilian (noninstitutionalized) population that involves interviews with approximately 67,000 randomly selected individuals 12 years of age and older. The data from NSDUH provide national- and state-level estimates on use of tobacco products, alcohol, illicit drugs (including nonmedical use of prescription drugs) and mental health in the United States. The restricted NSDUH data set contains state and substate identifiers (e.g., county, metropolitan statistical area) that permit evaluation of state-level policies that can influence individual-level substance use attitudes and behaviors. Details about NSDUH design can be found elsewhere (Substance Abuse and Mental Health Services Administration, 2015). For the current study, we combined the restricted data from 2004 to 2014. As shown in Fig. 1, this period encompassed the implementation of 36 state PDMPs, and 2014 was the most recent year for which data are available.

2.2. Measures

We examined three categories of outcomes: NMPR use, heroin use, and sources of NMPR for misuse. To assess NMPR use, NSDUH asks the respondent if they used prescription pain relievers *without a doctor's prescription* or *purely for the feeling or effects*. The question wording leaves the interpretation of NMPR as using prescription pain relievers for self-treatment or euphoria, using medication that could have been obtained with a doctor's prescription or acquired using some other method. We examined four outcomes associated with NMPR: (1) past-year NMPR use, (2) past-year DSM-IV abuse or dependence of NMPR, (3) past-year NMPR initiation based on respondents' answers to dates of first use, and (4) past-year days of NMPR use. The past-year initiation measure excludes users who began using NMPRs before the past year, so that recent initiates are compared to never-users. We created identical measures of past-year heroin use, abuse/dependence, initiation, and days of use from analogous NSDUH measures.

NSDUH also asks respondents reporting past-month use of NMPRs how they obtained the medication. These questions were added to the NSDUH questionnaire in 2005; thus, 2004 respondents are excluded from the analyses of these outcomes. Respondents are asked to identify as many sources as they used to obtain their drugs in the past month from the following list: one doctor, two or more doctors, from fake prescriptions, by theft, from friends/relatives (bought, stolen, or received for free are separate options), from a dealer/stranger, or from the internet. From these, we created four measures: (1) receipt from two or more prescribers, (2) receipt from two or more prescribers or fake prescriptions, (3) receipt from social sources (i.e., bought, stolen, or received for free from friends or family), (4) and receipt from illegitimate sources (i.e., stolen from a pharmacy, bought from a dealer, or obtained on the internet).

The independent variables of interest were measures of PDMP implementation at the state level. We created a binary measure, where 1 represents an operational PDMP in the respondent's state for the calendar quarter in which the interview took place, based on dates of PDMP implementation obtained from Brandeis's PDMP Training and Technical Assistance Center (2016) and the National Alliance for Model State Drug Laws (NAMSDL, 2014b). A second, categorical measure divided PDMPs into groups based on whether or not they had provisions requiring mandatory access by providers and/or mandatory prescriber enrollment. Dates of enactment of these provisions, which were often added to an existing PDMP, were obtained from NAMSDL

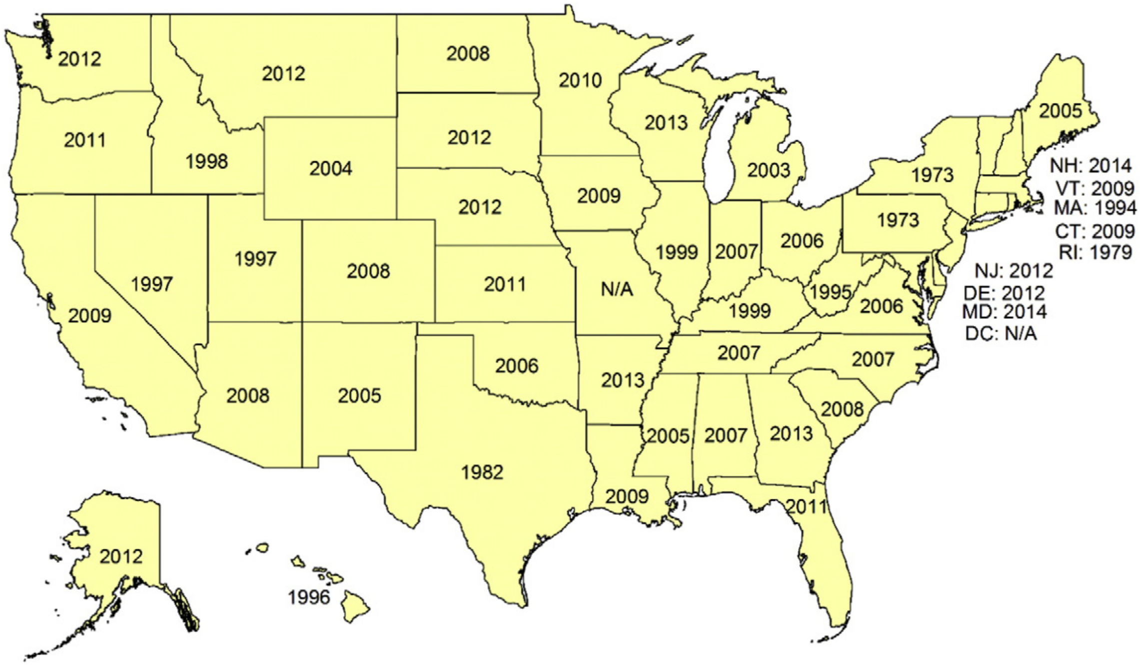

Fig. 1. PDMP implementation years by state.

(2014c). Additional control variables included a binary measure representing the existence of pain management clinic regulation in the respondent's state (NAMSDL, 2014a), a binary indicator for the calendar quarter of PDMP implementation, and demographic characteristics of the respondents.

2.3. Analysis

We pooled responses to the 2004–2014 NSDUH into a single dataset of repeated cross-sections of the civilian household population (N = 507,000). We estimated multivariable models of the 12 outcome measures described above, with each of the two measures of PDMP implementation (binary and categorical). For each outcome and PDMP measure combination, we estimated two models. Our primary model excluded respondents interviewed within the first year of the PDMP's existence in a state. Prior studies have shown that policy initiatives such as PDMPs require a year to become fully operational (Bao et al., 2016). In our secondary model, we repeated the analysis for all respondents. For the past-year heroin initiation outcome, we repeated these two models including only respondents who reported lifetime use of NMPRs. Models of binary outcomes (past-year use, abuse/dependence, initiation, and the NMPR source outcomes) were estimated using logit regression. Continuous outcomes were estimated using gamma generalized linear models with a log-link function due to the positive skew present in the distributions of past-year days of use of NMPR and heroin. Both binary and continuous outcomes were modeled with accommodations for the NSDUH sampling structure and analysis weights, and included state and time fixed effects (quarter) and state-specific linear time trends to control for differences across states and years. Descriptive statistics on the study sample and the variables used in the analysis are provided in Table 1.

3. Results

NMPR outcomes related to past-year use, past-year dependence/abuse and past-year initiation did not exhibit any significant association

Table 1
Descriptive statistics for 2002–2014 NSDUH respondents 18 years and older.

	All respondents (N = 507,000) Weighted mean	Exclude first year of PDMP (N = 480,000) Weighted mean
Male	0.482	0.482
Age		
18–25	0.148	0.147
26–34	0.159	0.159
35–49	0.277	0.277
50–64	0.246	0.246
65+	0.170	0.170
Race/ethnicity		
White, non-Hispanic	0.680	0.680
Black, non-Hispanic	0.115	0.115
Other, non-Hispanic	0.066	0.066
Hispanic	0.139	0.139
PDMP status		
PDMP in effect	0.639	0.625
PDMP w/o enhancements	0.551	0.534
PDMP w/mandatory access	0.038	0.040
PDMP w/mandatory enrollment	0.029	0.029
PDMP w/mandatory access/enrollment	0.021	0.022
Past-year substance outcomes		
NMPR use	0.045	0.045
NMPR abuse/dependence	0.007	0.007
NMPR initiation	0.006	0.006
NMPR days of use, conditional on any	47.862 (84.952)	47.709 (85.329)
Heroin use	0.002	0.002
Heroin abuse/dependence	0.002	0.002
Heroin initiation	0.001	0.001
Heroin days of use, conditional on any	110.065 (141.942)	108.675 (140.888)
Source of drugs among past-month NMPR users		
2+ doctors	0.053	0.053
2+ doctors and fake prescriptions	0.056	0.055
Social sources	0.727	0.728
Illegitimate sources	0.136	0.136

Weighted means with standard deviation in parentheses.

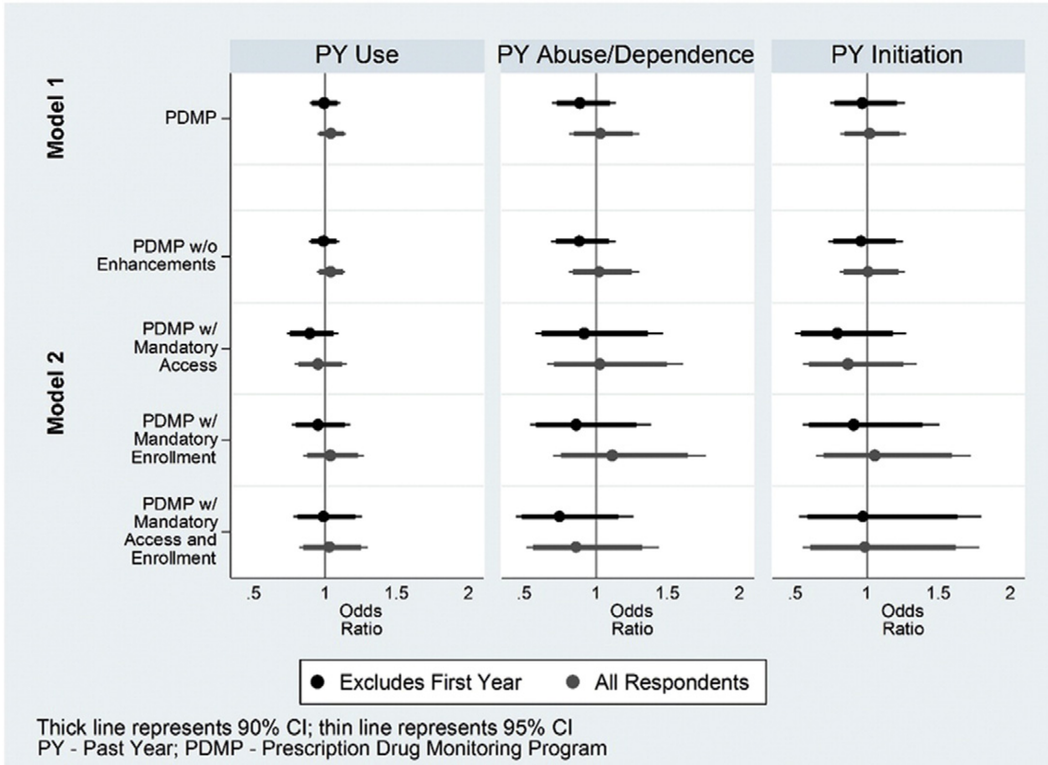

Fig. 2. Associations among PDMP status and NMPR binary outcomes.

with the two measures of PDMP implementation (Fig. 2). Even when the first year of PDMP implementation was excluded, neither the binary PDMP measure nor the categorical PDMP measure was statistically significant. The associations between pain management regulation and NMPR outcomes were also not statistically significant. PDMP implementation (excluding first year of implementation) was, however,

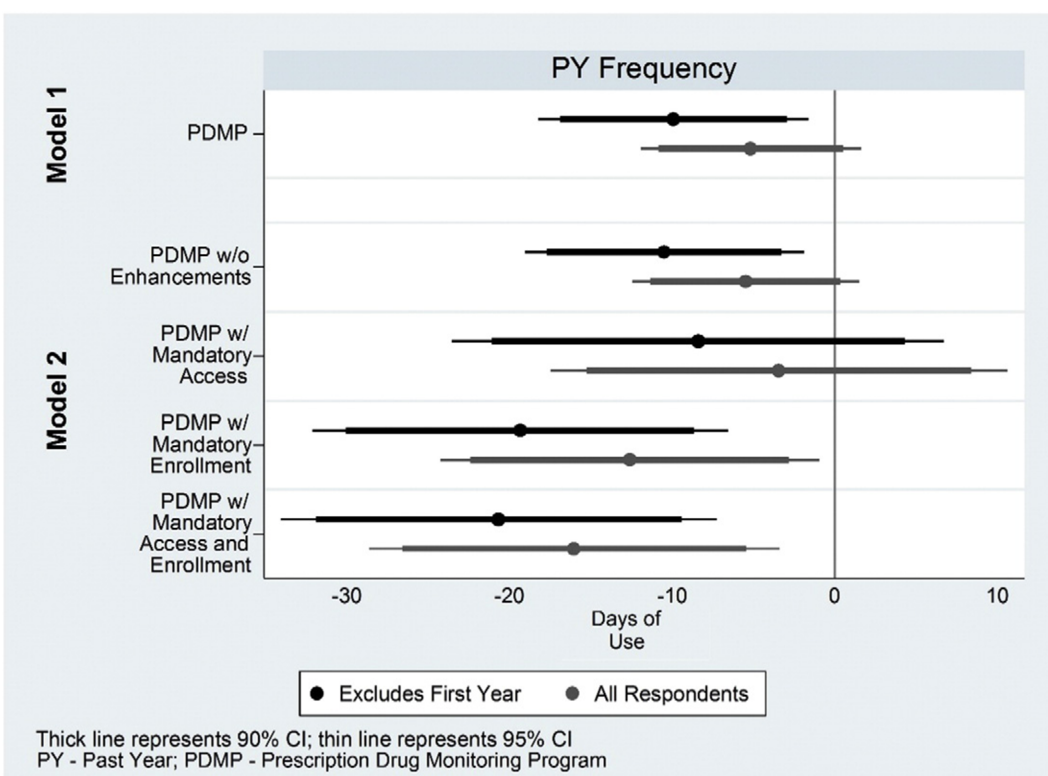

Fig. 3. Association between PDMP status and past-year frequency of NMPR use.

statistically significant in reducing the number of days of past-year NMPR use (Fig. 3). This association is present for both the binary measure and the categorical measure of PDMP implementation. Specifically, having an operational PDMP is associated with a reduction of approximately 10 days ($p < 0.05$) of use of NMPR in the past year. The categorical measure of PDMP indicates a reduction of approximately 20 days in past-year NMPR use ($p < 0.01$) when PDMPs have provisions that require mandatory enrollment and access by the providers.

Similar to NMPR outcomes, there was little systematic association between PDMP implementation and heroin-related outcomes (Fig. 4). Past-year use, past-year dependence, and past-year initiation did not exhibit any statistical association with either the binary PDMP implementation measure or the categorical implementation measure. However, having a PDMP without mandatory access and enrollment was statistically significant for past-year days of heroin use (Fig. 5). Having an operational pain management regulation was associated with past year heroin use and initiation (as shown in the results reported in Appendix 2).

Having a PDMP was associated with a reduction in receipt of pain relievers for nonmedical use from two or more doctors in the model that excludes the first year of PDMP implementation (Fig. 6). Specifically, having a PDMP with mandatory access provision is associated with an 80% reduction in the odds of having two or more doctors as a source of NMPR ($p < 0.05$). PDMPs without provisions of mandatory enrollment or access are associated with a 56% reduction in the odds of having two or more doctors as a source ($p < 0.05$). Similarly, PDMPs with a mandatory access provision and without any access or enrollment provisions were associated with 75% and 50% reductions in the odds of having a fake prescription or more than two doctors as a source of NMPR, respectively ($p < 0.10$). PDMPs were not significantly associated with having social sources or illegitimate sources as a means of obtaining NMPR.

4. Discussion

In this study, we utilized state-level variation in implementation of PDMPs and PDMP characteristics to investigate its impact on NMPR, sources of NMPR, and heroin use. We do not find significant associations between PDMP implementation or associated features of the monitoring programs on the nonmedical use, initiation, and abuse of prescription painkillers. However, we do find some evidence that PDMPs are associated with 10–20 fewer days of NMPR use. Our results also suggest that PDMP implementation was associated with reduced doctor shopping for prescription opiate painkillers. In addition, we find that implementation of PDMPs did not lead to an increase in heroin use or initiation, but was associated with an increase in number of days of heroin use in the past year.

The PDMP features found to be associated with the reduction in NMPR days of use and doctor shopping were mandatory enrollment and mandatory access by prescribers. This finding highlights that, as states continue to adopt and incorporate different features into their PDMPs, the effectiveness of their PDMPs is likely to increase. This is also encouraging in light of recent initiatives to require prescribers in the Indian Health Services and Veterans Affairs health systems to check state PDMPs before prescribing opioid painkillers (The White House, 2016). As these initiatives continue to expand to other health care delivery systems, more widespread adoption and utilization of PDMPs are expected.

Since 2010, heroin overdoses have been rising and, given the relatively lower price and increasing accessibility of heroin relative to prescription painkillers, concerns have arisen that the implementation of PDMPs may be driving the substitution of heroin for prescription painkillers (Muhuri et al., 2013). Our results do not generally support this theory, because PDMPs were not associated with higher levels of heroin use, abuse/dependence, or initiation. The transition from nonmedical

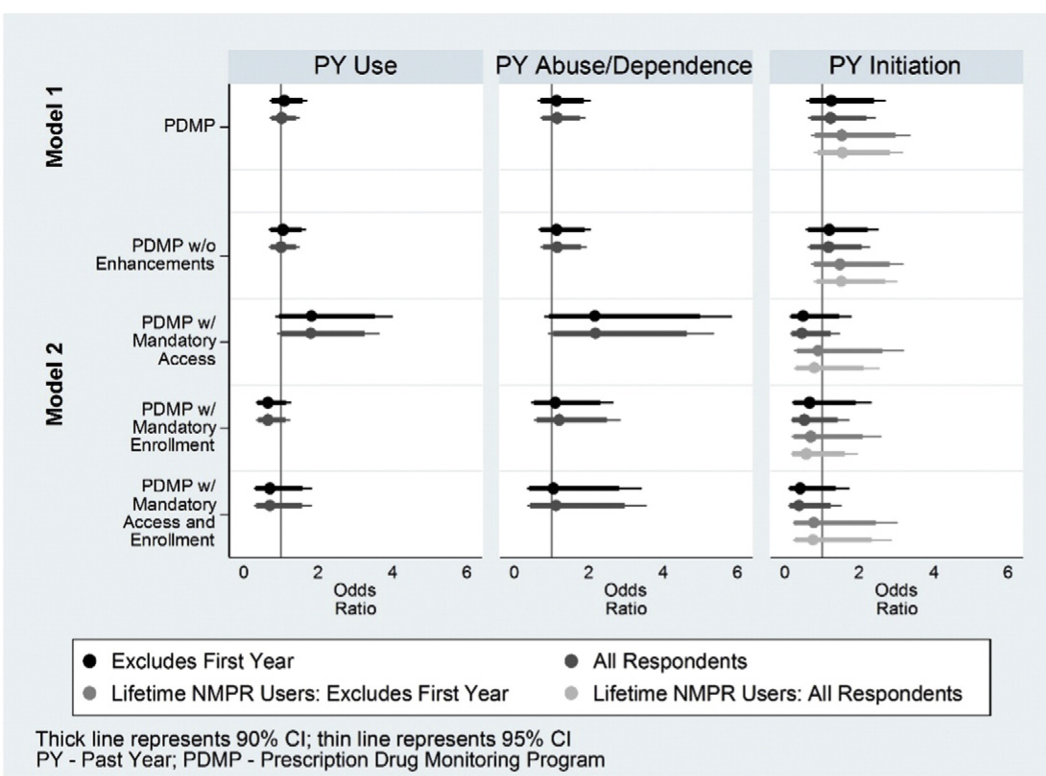

Fig. 4. Associations among PDMP status and heroin binary outcomes.

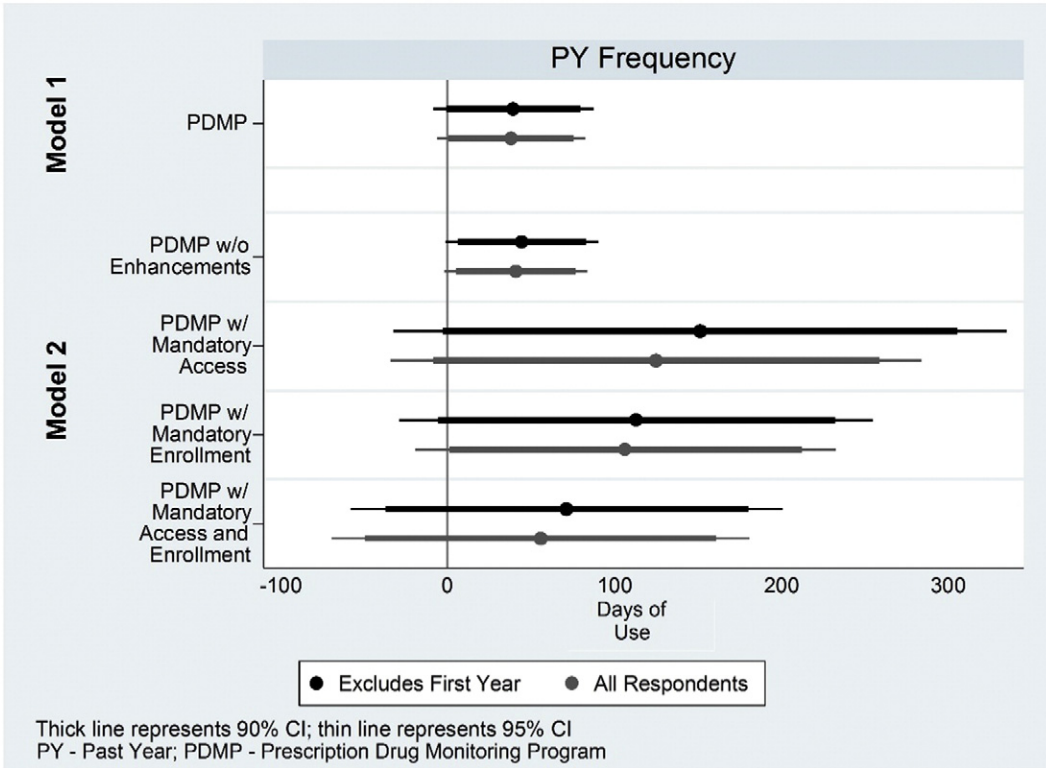

Fig. 5. Association between PDMP status and past-year frequency of heroin use.

opioid use to heroin use appears to be occurring only among a subgroup of nonmedical opioid users (Compton et al., 2016). Thus, the lack of association between heroin use and state PDMP status is not unexpected and does not appear to be related to the overall increases in rates of heroin use, although we did find some evidence of an association between PDMPs and past year frequency of heroin use. The Office of National

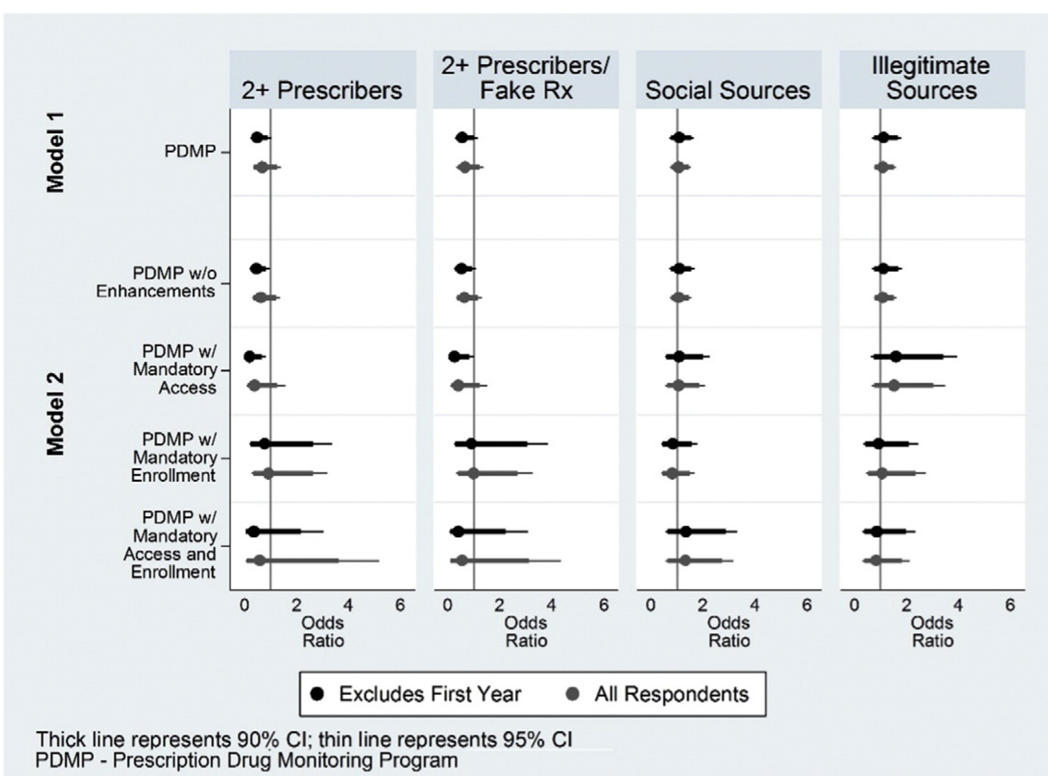

Fig. 6. Associations among PDMP status and sources of NMPR acquisition.

Drug Control Policy identified the goal of curbing multiple providers with overlapping prescriptions as one of the primary objectives of PDMPs (Simeone, 2014). Our finding that PDMP implementation was associated with a reduction in having two or more providers as a source for obtaining opioids and writing fake prescriptions implies that PDMP implementation might be associated with a reduction in doctor shopping behavior.

This study has a few important limitations. First, the NSDUH does not survey the same individuals from year to year. In addition, many opioid related policies have been implemented during our study period (e.g., abuse deterrent formulations of opioids, increased access to medication assisted treatment, changes in emphasizing pain as the fifth vital sign that should receive opioid prescriptions, etc.) which we have not been able to explicitly account for. However, we did control for potential respondent- and state-level confounders in our models. Second, we recognize that some states varied in the duration of their implementation period. We addressed this by estimating models that both excluded and included survey respondents in the first year of their home state's PDMP. Our results were generally not sensitive to the inclusion or exclusion of this group. Finally, we acknowledge that details of provisions requiring mandatory prescriber access or enrollment vary from state to state, and these details may affect the importance of the provision. Limits on the availability of data on PDMP characteristics and estimation problems (e.g., multicollinearity) introduced when too many PDMP characteristics are included in the model led us to the specification described here. Despite these limitations, this study contributes to the understanding of how PDMPs have affected the initiation and intensity of use of prescription opiate painkillers (when used nonmedically) and potential substitution to heroin when access to such painkillers is disrupted. To our knowledge, this is the only study to consider associations between PDMP characteristics and these patient outcomes.

5. Conclusion

Given the tremendous amount of morbidity and mortality associated with the opioid epidemic, the need for effective policy responses to this crisis is apparent (Centers for Disease Control and Prevention, 2016). The presence of PDMPs has expanded rapidly across states since 2000, but the literature has exhibited mixed evidence about their effectiveness (Bao et al., 2016; Chang et al., 2016; Meara et al., 2016). Our results indicate that mandating prescriber participation in the PDMP may be one avenue for reducing negative events resulting from opiate painkiller prescribing. While PDMPs are a policy tool targeted primarily toward prescribers, our results suggest the need for other initiatives to reduce the current level of opiate misuse in the United States. For example, less than a quarter of the patients with opioid-related hospitalizations had any post-discharge treatment engagement within 30 days of discharge (Ali & Mutter, 2016; Naeger, Ali, Mutter, Mark, & Hughey, 2016a) and only 17% of them received any FDA approved opioid dependence medication within 30 days of discharge (Naeger, Ali, Mutter, Mark, & Hughey, 2016b). This presents an opportunity for implementing better health system related policy initiatives to enable the patients to get appropriate treatment. Other initiatives, such as expanding availability of medication-assisted treatment and other substance abuse treatment provisions in the Comprehensive Addiction and Recovery Act (CARA), signed by President Obama in July 2016, and the $1 billion in grants to help states address opioid misuse in the 21st Century Cures Act, signed by President Obama in December 2016, may also help to stem this public health crisis. Also, some states have recently passed legislation limiting the days supplied of prescribed pain medications, except for certain circumstances (Connecticut General Assembly, 2016). Prescriber-oriented initiatives, such as PDMPs, can help curb the opioid crisis by providing physicians, pharmacists, and other health care providers access to patients' prescription histories and helping to identify individuals at risk of opioid misuse; nevertheless, a multilevel policy approach that engages all sectors of the health service system, which addresses various aspects of the crisis, including prevention of misuse initiation, is warranted. As such, tackling this issue requires not only effective PDMPs but also educational efforts to raise awareness among patients and health care providers. This analysis provides further evidence that PDMPs are one such effective policy tool.

Disclaimer

The views expressed here are those of the authors and do not necessarily reflect the views of the Substance Abuse and Mental Health Services Administration (SAMHSA) or the U.S. Department of Health and Human Services (DHHS).

Financial disclosure statement

Mir M. Ali, William N. Dowd, Timothy Classen, Ryan Mutter and Scott P. Novak have no financial disclosures relevant to this article.

Appendix 1. NMPD outcomes

	NMPD - Past Year Use				NMPD - Past Year Abuse/Dependence				NMPD - Past Year Initiation				Average PY Days of Use: NMPD			
	All Respondents		Exclude First Year of PDMP		All Respondents		Exclude First Year of PDMP		All Respondents		Exclude First Year of PDMP		All Respondents		Exclude First Year of PDMP	
State PDMP Active	1.041		0.993		1.03		0.888		1.018		0.968		-5.163		-9.929**	
	[0.947,1.145]		[0.893,1.104]		[0.814,1.304]		[0.694,1.137]		[0.815,1.272]		[0.742,1.263]		[3.454]		[4.235]	
PDMP w/o Enhancements		1.038		0.988		1.024		0.885		1.01		0.959		-5.489		-10.478**
		[0.943,1.141]		[0.888,1.099]		[0.808,1.297]		[0.689,1.136]		[0.807,1.264]		[0.734,1.252]		[3.554]		[4.374]
PDMP w/ Mandatory Access		0.952		0.895		1.026		0.918		0.865		0.794		-3.428		-8.401
		[0.787,1.152]		[0.733,1.092]		[0.656,1.607]		[0.575,1.467]		[0.555,1.349]		[0.496,1.273]		[7.167]		[7.723]
PDMP w/ Mandatory Enrollment		1.036		0.952		1.112		0.864		1.055		0.909		-12.608**		-19.315***
		[0.847,1.266]		[0.770,1.176]		[0.700,1.766]		[0.541,1.382]		[0.645,1.724]		[0.549,1.505]		[5.942]		[6.509]
PDMP w/ Mandatory Access and Enrollment		1.028		0.988		0.861		0.746		0.988		0.976		-15.999**		-20.653***
		[0.816,1.296]		[0.776,1.256]		[0.516,1.437]		[0.442,1.260]		[0.548,1.780]		[0.529,1.800]		[6.427]		[6.830]
Pain Management Regulation = 1	1.019	1.031	1.016	1.027	1.079	1.113	1.056	1.084	1.181	1.21	1.159	1.188	3.106	4.766	-0.408	1.104
	[0.893,1.162]	[0.899,1.182]	[0.886,1.165]	[0.892,1.183]	[0.823,1.413]	[0.823,1.505]	[0.798,1.398]	[0.794,1.480]	[0.837,1.666]	[0.845,1.731]	[0.816,1.647]	[0.825,1.710]	[4.443]	[4.855]	[4.373]	[4.761]
First Quarter of PDMP Implementation = 1	1.003	1	0.992	0.99	0.865	0.862	0.875	0.869	0.882	0.877	0.831	0.827	-7.188	-7.422	-5.431	-5.909
	[0.864,1.163]	[0.861,1.161]	[0.791,1.245]	[0.788,1.242]	[0.588,1.274]	[0.585,1.270]	[0.476,1.608]	[0.472,1.601]	[0.615,1.266]	[0.611,1.259]	[0.426,1.621]	[0.425,1.610]	[4.592]	[4.596]	[6.651]	[6.589]
Male = 1	1.310***	1.310***	1.300***	1.300***	1.523***	1.523***	1.527***	1.527***	0.887***	0.887***	0.879***	0.879***	8.766***	8.733***	8.418***	8.386***
	[1.262,1.359]	[1.262,1.359]	[1.252,1.350]	[1.252,1.350]	[1.399,1.659]	[1.399,1.659]	[1.399,1.666]	[1.399,1.666]	[0.815,0.966]	[0.815,0.966]	[0.807,0.957]	[0.807,0.957]	[1.241]	[1.240]	[1.259]	[1.258]
Age 26-34	0.610***	0.610***	0.606***	0.606***	0.720***	0.720***	0.705***	0.705***	0.277***	0.277***	0.276***	0.276***	4.785***	4.741***	4.761***	4.708***
	[0.585,0.635]	[0.585,0.635]	[0.581,0.631]	[0.581,0.631]	[0.653,0.794]	[0.653,0.793]	[0.640,0.778]	[0.640,0.778]	[0.244,0.315]	[0.244,0.315]	[0.243,0.314]	[0.243,0.314]	[1.516]	[1.512]	[1.610]	[1.605]
Age 35-49	0.340***	0.340***	0.339***	0.339***	0.355***	0.355***	0.357***	0.357***	0.118***	0.118***	0.116***	0.116***	1.177	1.238	1.395	1.474
	[0.325,0.355]	[0.325,0.355]	[0.324,0.354]	[0.324,0.354]	[0.318,0.396]	[0.318,0.396]	[0.319,0.399]	[0.319,0.399]	[0.103,0.136]	[0.103,0.136]	[0.101,0.135]	[0.101,0.135]	[1.582]	[1.583]	[1.630]	[1.632]
Age 50-64	0.172***	0.172***	0.166***	0.166***	0.181***	0.181***	0.179***	0.179***	0.055***	0.055***	0.054***	0.054***	4.738	4.724	5.223*	5.250*
	[0.159,0.187]	[0.159,0.187]	[0.153,0.180]	[0.153,0.180]	[0.147,0.224]	[0.146,0.224]	[0.145,0.221]	[0.145,0.221]	[0.042,0.073]	[0.042,0.073]	[0.041,0.071]	[0.041,0.071]	[2.897]	[2.898]	[2.950]	[2.954]
Age 65 +	0.048***	0.048***	0.048***	0.048***	0.042***	0.042***	0.044***	0.044***	0.005***	0.005***	0.004***	0.004***	6.723	6.698	6.226	6.109
	[0.040,0.057]	[0.040,0.057]	[0.040,0.058]	[0.040,0.058]	[0.025,0.070]	[0.025,0.070]	[0.026,0.073]	[0.026,0.073]	[0.002,0.013]	[0.002,0.013]	[0.001,0.011]	[0.001,0.011]	[6.642]	[6.583]	[6.938]	[6.863]
Black, non-hispanic	0.628***	0.628***	0.621***	0.621***	0.591***	0.591***	0.611***	0.611***	0.692***	0.692***	0.658***	0.658***	7.113***	7.056***	6.990***	6.906***
	[0.585,0.675]	[0.585,0.675]	[0.577,0.669]	[0.577,0.670]	[0.484,0.723]	[0.484,0.723]	[0.497,0.750]	[0.497,0.750]	[0.598,0.800]	[0.598,0.800]	[0.573,0.757]	[0.573,0.757]	[2.031]	[2.026]	[2.104]	[2.097]
Other, non-hispanic	0.549***	0.549***	0.519***	0.519***	0.592***	0.592***	0.626***	0.626***	0.482***	0.482***	0.466***	0.466***	1.71	1.981	2.282	2.621
	[0.497,0.607]	[0.497,0.607]	[0.471,0.571]	[0.471,0.571]	[0.481,0.730]	[0.481,0.730]	[0.507,0.772]	[0.507,0.772]	[0.392,0.593]	[0.392,0.593]	[0.375,0.581]	[0.375,0.581]	[3.005]	[3.005]	[3.122]	[3.131]
Hispanic	0.631***	0.631***	0.632***	0.633***	0.549***	0.549***	0.545***	0.545***	0.496***	0.496***	0.482***	0.483***	4.139*	4.135*	4.371*	4.337*
	[0.592,0.673]	[0.592,0.673]	[0.593,0.675]	[0.593,0.675]	[0.465,0.649]	[0.465,0.649]	[0.464,0.641]	[0.464,0.641]	[0.431,0.572]	[0.431,0.572]	[0.417,0.558]	[0.417,0.558]	[2.357]	[2.355]	[2.360]	[2.358]
Constant	0.115***	0.116***	0.120***	0.120***	0.025***	0.025***	0.024***	0.024***	0.050***	0.051***	0.050***	0.049***				
	[0.086,0.154]	[0.086,0.156]	[0.089,0.162]	[0.089,0.162]	[0.013,0.047]	[0.013,0.049]	[0.013,0.047]	[0.013,0.047]	[0.024,0.106]	[0.024,0.109]	[0.023,0.108]	[0.022,0.109]				
Observations	507,000	507,000	480,000	480,000	507,000	507,000	480,000	480,000	417,000	417,000	395,000	395,000	37,000	37,000	35,000	35,000

Binary outcome models show odds ratios from logit regressions with confidence intervals presented in brackets.
Continuous outcome models show marginal effects from Gamma GLM regressions with standard errors presented in brackets.
Models include state and time (qtr) fixed effects, as well as state-specific time (qtr) trends.
NMPD - Non-Medical Prescription Drug; PY - Past Year; PDMP - Prescription Drug Monitoring Program.
* p<0.10, ** p<0.05, *** p<0.01.

Appendix 2. Heroin outcomes

	Heroin - Past Year Use				Heroin - Past Year Abuse/Dependence			
	All Respondents		Exclude First Year of PDMP		All Respondents		Exclude First Year of PDMP	
State PDMP Active	1.02		1.079		1.148		1.135	
	[0.691,1.507]		[0.686,1.699]		[0.692,1.906]		[0.630,2.043]	
PDMP w/o Enhancements		1.008		1.057		1.161		1.144
		[0.680,1.496]		[0.668,1.674]		[0.696,1.938]		[0.632,2.072]
PDMP w/ Mandatory Access		1.802		1.828		2.191*		2.162
		[0.892,3.640]		[0.840,3.982]		[0.894,5.367]		[0.799,5.850]
PDMP w/ Mandatory Enrollment		0.65		0.649		1.214		1.096
		[0.336,1.256]		[0.330,1.277]		[0.516,2.855]		[0.452,2.661]
PDMP w/ Mandatory Access and Enrollment		0.715		0.707		1.116		1.057
		[0.280,1.825]		[0.271,1.840]		[0.349,3.566]		[0.327,3.413]
Pain Management Regulation = 1	1.749**	1.671	1.729**	1.682	1.49	1.353	1.473	1.358
	[1.018,3.006]	[0.892,3.129]	[1.002,2.985]	[0.890,3.176]	[0.723,3.071]	[0.590,3.106]	[0.722,3.003]	[0.594,3.101]
First Quarter of PDMP Implementation = 1	1.054	1.066	0.948	0.917	1.121	1.149	0.886	0.883
	[0.554,2.005]	[0.558,2.036]	[0.403,2.229]	[0.386,2.176]	[0.476,2.638]	[0.487,2.711]	[0.235,3.341]	[0.233,3.349]
Male = 1	2.302***	2.301***	2.322***	2.322***	2.268***	2.268***	2.296***	2.295***
	[1.991,2.660]	[1.991,2.660]	[2.001,2.694]	[2.001,2.694]	[1.899,2.711]	[1.898,2.710]	[1.914,2.754]	[1.914,2.753]
Age 26-34	0.791***	0.791***	0.811**	0.811**	0.898	0.898	0.914	0.914
	[0.672,0.930]	[0.673,0.931]	[0.687,0.958]	[0.687,0.958]	[0.738,1.092]	[0.738,1.092]	[0.749,1.116]	[0.749,1.117]
Age 35-49	0.309***	0.309***	0.310***	0.310***	0.360***	0.360***	0.351***	0.350***
	[0.256,0.372]	[0.256,0.372]	[0.256,0.375]	[0.256,0.375]	[0.284,0.457]	[0.284,0.457]	[0.274,0.448]	[0.274,0.448]
Age 50-64	0.171***	0.171***	0.174***	0.174***	0.193***	0.193***	0.196***	0.196***
	[0.120,0.245]	[0.120,0.245]	[0.120,0.252]	[0.120,0.252]	[0.124,0.300]	[0.124,0.300]	[0.124,0.309]	[0.124,0.309]
Age 65 +	0.024***	0.024***	0.026***	0.026***	0.033***	0.033***	0.035***	0.035***
	[0.009,0.065]	[0.009,0.065]	[0.010,0.070]	[0.010,0.070]	[0.010,0.103]	[0.010,0.103]	[0.011,0.111]	[0.011,0.111]
Black, non-hispanic	0.873	0.873	0.898	0.898	0.852	0.852	0.861	0.861
	[0.662,1.152]	[0.661,1.151]	[0.675,1.194]	[0.675,1.193]	[0.615,1.182]	[0.615,1.181]	[0.614,1.208]	[0.615,1.207]
Other, non-hispanic	0.340***	0.340***	0.292***	0.292***	0.266***	0.266***	0.187***	0.187***
	[0.230,0.502]	[0.230,0.501]	[0.203,0.421]	[0.203,0.420]	[0.147,0.483]	[0.147,0.482]	[0.111,0.314]	[0.111,0.314]
Hispanic	0.736*	0.736*	0.774	0.774	0.841	0.841	0.877	0.876
	[0.534,1.015]	[0.534,1.014]	[0.557,1.076]	[0.557,1.075]	[0.569,1.242]	[0.569,1.242]	[0.586,1.311]	[0.586,1.311]
Constant	0.006***	0.005***	0.006***	0.005***	0.003***	0.003***	0.003***	0.003***
	[0.002,0.017]	[0.002,0.016]	[0.002,0.017]	[0.002,0.016]	[0.000,0.018]	[0.000,0.018]	[0.001,0.019]	[0.001,0.019]
Observations	507,000	507,000	480,000	480,000	507,000	507,000	480,000	480,000

(continued on next page)

Appendix 2 (*continued*)

	Heroin - Past Year Initiation								Average PY Days of Use: Heroin			
	All Respondents		All NMPD Users		Exclude First Year of PDMP		Exclude First Year of PDMP, NMPD Users		All Respondents		Exclude First Year of PDMP	
State PDMP Active	1.228		1.556		1.247		1.53		38.310*		39.665	
	[0.616,2.447]		[0.767,3.159]		[0.576,2.702]		[0.696,3.364]		[22.714]		[24.508]	
PDMP w/o Enhancements		1.18		1.515		1.184		1.474		41.036*		44.614*
		[0.609,2.284]		[0.764,3.004]		[0.559,2.509]		[0.684,3.178]		[21.911]		[23.398]
PDMP w/ Mandatory Access		0.456		0.791		0.484		0.89		125.193		151.543
		[0.140,1.486]		[0.245,2.552]		[0.131,1.786]		[0.247,3.201]		[81.146]		[93.700]
PDMP w/ Mandatory Enrollment		0.518		0.565		0.656		0.684		106.804*		113.158
		[0.156,1.720]		[0.163,1.955]		[0.186,2.318]		[0.181,2.584]		[64.236]		[72.361]
PDMP w/ Mandatory Access and Enrollment		0.383		0.766		0.41		0.783		55.991		71.552
		[0.097,1.518]		[0.205,2.867]		[0.098,1.724]		[0.202,3.027]		[63.780]		[65.971]
Pain Management Regulation = 1	2.864***	4.476***	3.343***	4.596***	2.958***	4.426***	3.332***	4.317***	-9.319	-19.285	-3.977	-15.367
	[1.311,6.258]	[1.881,10.649]	[1.363,8.200]	[1.736,12.173]	[1.344,6.508]	[1.869,10.484]	[1.362,8.155]	[1.646,11.319]	[45.729]	[42.304]	[47.859]	[43.591]
First Quarter of PDMP Implementation = 1	1.665	1.569	1.474	1.409	1.866	1.782	1.7	1.639	-59.202**	-57.091**	-84.865***	-80.884***
	[0.707,3.925]	[0.668,3.689]	[0.559,3.890]	[0.535,3.710]	[0.588,5.920]	[0.562,5.651]	[0.468,6.175]	[0.451,5.961]	[23.643]	[24.043]	[13.386]	[15.164]
Male = 1	1.697***	1.697***	1.361**	1.359**	1.677***	1.677***	1.333**	1.331**	-17.223*	-16.599*	-22.821**	-21.948**
	[1.338,2.152]	[1.338,2.152]	[1.059,1.749]	[1.057,1.748]	[1.315,2.140]	[1.315,2.139]	[1.030,1.724]	[1.029,1.722]	[9.894]	[9.850]	[10.272]	[10.234]
Age 26-34	0.364***	0.364***	0.371***	0.373***	0.370***	0.370***	0.376***	0.377***	-6.618	-6.459	-4.194	-4.201
	[0.248,0.535]	[0.247,0.536]	[0.244,0.564]	[0.245,0.567]	[0.250,0.547]	[0.250,0.547]	[0.245,0.576]	[0.246,0.579]	[12.342]	[12.191]	[12.375]	[12.223]
Age 35-49	0.120***	0.120***	0.137***	0.138***	0.115***	0.115***	0.130***	0.131***	-8.817	-8.57	-16.775	-16.675
	[0.078,0.185]	[0.078,0.185]	[0.083,0.226]	[0.083,0.227]	[0.073,0.181]	[0.073,0.181]	[0.077,0.219]	[0.078,0.220]	[17.314]	[17.265]	[16.897]	[16.828]
Age 50-64	0.009***	0.009***	0.015***	0.015***	0.009***	0.009***	0.016***	0.016***	-48.669***	-48.647***	-39.803**	-39.135**
	[0.002,0.039]	[0.002,0.039]	[0.002,0.107]	[0.002,0.107]	[0.002,0.042]	[0.002,0.042]	[0.002,0.115]	[0.002,0.115]	[18.749]	[18.679]	[19.810]	[19.709]
Age 65 +	1	1	1	1	1	1	1	1	-39.046**	-42.461**	-36.949**	-40.474**
	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[17.989]	[17.706]	[17.976]	[17.850]
Black, non-hispanic	0.158***	0.158***	0.264**	0.263**	0.116***	0.116***	0.178***	0.177***	58.841***	58.504***	52.176***	51.923***
	[0.061,0.412]	[0.061,0.412]	[0.091,0.761]	[0.091,0.757]	[0.040,0.337]	[0.040,0.337]	[0.051,0.627]	[0.051,0.623]	[18.126]	[18.208]	[17.553]	[17.643]
Other, non-hispanic	0.357***	0.357***	0.761	0.765	0.364***	0.365***	0.768	0.77	47.08	45.281	24.956	23.092
	[0.185,0.686]	[0.185,0.687]	[0.393,1.473]	[0.396,1.476]	[0.183,0.724]	[0.183,0.725]	[0.383,1.539]	[0.385,1.541]	[31.091]	[31.707]	[36.876]	[37.963]
Hispanic	0.385***	0.385***	0.566***	0.568***	0.401***	0.402***	0.580**	0.583**	-9.348	-10.088	-15.149	-15.105
	[0.262,0.564]	[0.263,0.564]	[0.377,0.850]	[0.378,0.853]	[0.273,0.591]	[0.273,0.591]	[0.383,0.879]	[0.385,0.883]	[18.046]	[18.097]	[18.366]	[18.359]
Constant	0.002***	0.001***	0.007***	0.006***	0.002***	0.002***	0.006***	0.006***				
	[0.000,0.014]	[0.000,0.013]	[0.001,0.057]	[0.001,0.052]	[0.000,0.014]	[0.000,0.013]	[0.001,0.057]	[0.001,0.052]				
Observations	460,000	460,000	86,000	86,000	437,000	437,000	81,000	81,000	2,000	2,000	1,900	1,900

Binary outcome models show odds ratios from logit regressions with confidence intervals presented in brackets.
Continuous outcome models show marginal effects from Gamma GLM regressions with standard errors presented in brackets.
Models include state and time (qtr) fixed effects, as well as state-specific time (qtr) trends.
PY - Past Year; PDMP - Prescription Drug Monitoring Program.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix 3. NMPD source outcomes

	NMPD Source: Two or More Doctors				NMPD Source: Dr Shopping/Fake Rx			
	All Respondents		Exclude First Year of PDMP		All Respondents		Exclude First Year of PDMP	
State PDMP Active	0.664		0.478*		0.667		0.55	
	[0.317,1.393]		[0.224,1.020]		[0.331,1.344]		[0.265,1.142]	
PDMP w/o Enhancements		0.634		0.438**		0.637		0.511*
		[0.294,1.367]		[0.205,0.935]		[0.309,1.313]		[0.245,1.065]
PDMP w/ Mandatory Access		0.375		0.198**		0.387		0.257*
		[0.090,1.557]		[0.048,0.823]		[0.100,1.493]		[0.065,1.007]
PDMP w/ Mandatory Enrollment		0.929		0.76		0.982		0.919
		[0.271,3.186]		[0.172,3.364]		[0.297,3.251]		[0.220,3.835]
PDMP w/ Mandatory Access and Enrollment		0.562		0.34		0.538		0.386
		[0.061,5.149]		[0.038,3.047]		[0.067,4.332]		[0.048,3.089]
Pain Management Regulation = 1	0.979	1.025	0.946	1.023	1.04	1.088	1.047	1.121
	[0.397,2.415]	[0.395,2.662]	[0.367,2.437]	[0.377,2.774]	[0.439,2.463]	[0.438,2.703]	[0.424,2.588]	[0.431,2.914]
First Quarter of PDMP Implementation = 1	0.321*	0.319*	0.269	0.263	0.324*	0.322*	0.291	0.287
	[0.093,1.107]	[0.092,1.102]	[0.038,1.891]	[0.037,1.880]	[0.095,1.101]	[0.094,1.098]	[0.042,1.997]	[0.041,2.000]
Male = 1	1.077	1.074	1.033	1.032	1.108	1.104	1.071	1.069
	[0.814,1.424]	[0.811,1.420]	[0.775,1.378]	[0.773,1.376]	[0.844,1.454]	[0.840,1.450]	[0.809,1.419]	[0.807,1.417]
Age 26-34	1.081	1.077	1.138	1.134	1.048	1.044	1.102	1.099
	[0.767,1.522]	[0.764,1.518]	[0.798,1.621]	[0.795,1.617]	[0.751,1.463]	[0.747,1.458]	[0.781,1.556]	[0.778,1.552]
Age 35-49	1.293	1.29	1.222	1.22	1.24	1.237	1.172	1.169
	[0.941,1.777]	[0.939,1.773]	[0.889,1.679]	[0.887,1.676]	[0.910,1.689]	[0.908,1.685]	[0.860,1.596]	[0.858,1.593]
Age 50-64	1.917***	1.938***	1.866**	1.892**	2.051***	2.076***	2.029***	2.058***
	[1.181,3.113]	[1.193,3.148]	[1.146,3.041]	[1.159,3.087]	[1.304,3.225]	[1.319,3.267]	[1.284,3.207]	[1.300,3.258]
Age 65 +	3.521***	3.540***	4.097***	4.117***	3.408***	3.432***	3.986***	4.011***
	[1.666,7.440]	[1.679,7.464]	[1.897,8.847]	[1.905,8.897]	[1.617,7.182]	[1.632,7.216]	[1.861,8.538]	[1.871,8.601]
Black, non-hispanic	1.833***	1.837***	1.981***	1.996***	1.833***	1.838***	1.968***	1.984***
	[1.237,2.716]	[1.239,2.724]	[1.326,2.958]	[1.334,2.987]	[1.249,2.689]	[1.252,2.699]	[1.332,2.907]	[1.340,2.936]
Other, non-hispanic	0.744	0.73	0.944	0.933	0.717	0.7	0.914	0.9
	[0.375,1.478]	[0.368,1.446]	[0.483,1.845]	[0.480,1.813]	[0.366,1.406]	[0.358,1.371]	[0.476,1.755]	[0.471,1.719]
Hispanic	0.841	0.847	0.92	0.935	0.859	0.866	0.934	0.95
	[0.490,1.444]	[0.493,1.455]	[0.529,1.602]	[0.536,1.632]	[0.508,1.455]	[0.511,1.467]	[0.544,1.604]	[0.553,1.634]
Constant	0.110***	0.129***	0.103***	0.126***	0.154***	0.183**	0.152***	0.187**
	[0.029,0.413]	[0.033,0.504]	[0.026,0.412]	[0.030,0.524]	[0.043,0.550]	[0.049,0.679]	[0.041,0.564]	[0.048,0.723]
Observations	12,000	12,000	11,000	11,000	12,000	12,000	11,000	11,000

(continued on next page)

Appendix 3 (*continued*)

	NMPD Source: 'Social' Sources				NMPD Source: Illegitimate Sources			
	All Respondents		Exclude First Year of PDMP		All Respondents		Exclude First Year of PDMP	
State PDMP Active	1.052		1.08		1.088		1.109	
	[0.727,1.523]		[0.706,1.650]		[0.740,1.600]		[0.687,1.791]	
PDMP w/o Enhancements		1.065		1.081		1.091		1.114
		[0.735,1.542]		[0.705,1.658]		[0.739,1.610]		[0.684,1.815]
PDMP w/ Mandatory Access		1.062		1.088		1.513		1.58
		[0.541,2.087]		[0.524,2.262]		[0.658,3.478]		[0.631,3.957]
PDMP w/ Mandatory Enrollment		0.803		0.829		1.08		0.911
		[0.386,1.672]		[0.386,1.781]		[0.425,2.746]		[0.340,2.444]
PDMP w/ Mandatory Access and Enrollment		1.326		1.346		0.817		0.855
		[0.559,3.143]		[0.549,3.302]		[0.317,2.103]		[0.314,2.329]
Pain Management Regulation = 1	0.825	0.799	0.803	0.774	1.408	1.442	1.297	1.321
	[0.504,1.350]	[0.471,1.354]	[0.482,1.339]	[0.448,1.336]	[0.850,2.331]	[0.837,2.487]	[0.772,2.180]	[0.751,2.323]
First Quarter of PDMP Implementation = 1	0.818	0.817	0.996	0.99	0.471**	0.472**	0.163***	0.162***
	[0.465,1.438]	[0.465,1.436]	[0.430,2.305]	[0.428,2.294]	[0.224,0.989]	[0.224,0.994]	[0.043,0.624]	[0.042,0.626]
Male = 1	0.816***	0.818***	0.847**	0.848**	1.639***	1.637***	1.649***	1.648***
	[0.709,0.939]	[0.710,0.941]	[0.734,0.978]	[0.734,0.979]	[1.383,1.943]	[1.382,1.940]	[1.384,1.965]	[1.384,1.964]
Age 26-34	0.926	0.929	0.893	0.894	0.693***	0.692***	0.713***	0.714***
	[0.784,1.094]	[0.786,1.097]	[0.754,1.057]	[0.755,1.058]	[0.574,0.836]	[0.574,0.836]	[0.587,0.864]	[0.588,0.866]
Age 35-49	0.674***	0.674***	0.694***	0.694***	0.387***	0.387***	0.394***	0.394***
	[0.573,0.793]	[0.573,0.793]	[0.587,0.820]	[0.587,0.820]	[0.310,0.483]	[0.310,0.484]	[0.312,0.496]	[0.313,0.497]
Age 50-64	0.502***	0.500***	0.529***	0.527***	0.406***	0.402***	0.452***	0.448***
	[0.383,0.657]	[0.382,0.654]	[0.401,0.698]	[0.399,0.696]	[0.266,0.620]	[0.264,0.613]	[0.294,0.695]	[0.292,0.686]
Age 65 +	0.147***	0.147***	0.145***	0.144***	0.259***	0.259***	0.212***	0.212***
	[0.083,0.263]	[0.083,0.262]	[0.077,0.271]	[0.077,0.270]	[0.098,0.688]	[0.098,0.689]	[0.070,0.647]	[0.069,0.648]
Black, non-hispanic	0.416***	0.415***	0.447***	0.445***	0.604***	0.605***	0.645**	0.645**
	[0.336,0.515]	[0.335,0.514]	[0.357,0.559]	[0.356,0.558]	[0.424,0.861]	[0.425,0.861]	[0.450,0.925]	[0.450,0.923]
Other, non-hispanic	0.458***	0.462***	0.511***	0.515***	0.869	0.866	0.933	0.937
	[0.320,0.654]	[0.324,0.660]	[0.359,0.728]	[0.361,0.734]	[0.574,1.314]	[0.575,1.306]	[0.614,1.419]	[0.618,1.419]
Hispanic	0.461***	0.459***	0.472***	0.469***	0.624***	0.625***	0.599***	0.599***
	[0.365,0.583]	[0.363,0.580]	[0.370,0.601]	[0.369,0.598]	[0.449,0.867]	[0.450,0.868]	[0.424,0.845]	[0.425,0.845]
Constant	4.180**	3.625**	4.111**	3.645**	0.240**	0.240**	0.217**	0.201**
	[1.367,12.786]	[1.175,11.180]	[1.357,12.454]	[1.193,11.137]	[0.072,0.800]	[0.069,0.837]	[0.062,0.751]	[0.056,0.728]
Observations	12,000	12,000	11,000	11,000	12,000	12,000	11,000	11,000

Odds ratios from logit regressions with confidence intervals presented in brackets.
Models include state and time (qtr) fixed effects, as well as state-specific time (qtr) trends.
Models are conditional on past-month NMPD use.
NMPD - Non-Medical Prescription Drug; PDMP - Prescription Drug Monitoring Program.
* p<0.10, ** p<0.05, *** p<0.01.

References

Ali, M. M., & Mutter, R. (2016). Patients who are privately insured receive limited follow-up services after opioid related hospitalizations. http://www.samhsa.gov/data/sites/default/files/report_2117/ShortReport-2117.html

Bao, Y., Pan, Y., Taylor, A., Radakrishnan, S., Luo, F., Pincus, H. A., & Schackman, B. R. (2016). Prescription drug monitoring programs are associated with sustained reductions in opioid prescribing by physicians. *Health Affairs (Project Hope)*, *35*, 1045–1051. http://dx.doi.org/10.1377/hlthaff.2015.1673.

Cai, R., Crane, E., Poneleit, K., & Paulozzi, L. (2010). Emergency department visits involving nonmedical use of selected prescription drugs in the United States, 2004-2008. *Journal of Pain & Palliative Care Pharmacotherapy*, *24*, 293–297. http://dx.doi.org/10.3109/15360288.2010.503730.

Centers for Disease Control and Prevention (2016). Policy impact: Prescription painkiller overdoses. http://www.cdc.gov/drugoverdose/index.html

Chang, H. -Y., Lyapustina, T., Rutkow, L., Daubresse, M., Richey, M., Faul, M., ... Alexander, G. C. (2016). Impact of prescription drug monitoring programs and pill mill laws on high-risk opioid prescribers: A comparative interrupted time series analysis. *Drug and Alcohol Dependence*, *165*, 1–8. http://dx.doi.org/10.1016/j.drugalcdep.2016.04.033.

Compton, W. M., Jones, C. M., & Baldwin, G. T. (2016). Relationship between nonmedical prescription-opioid use and heroin use. *The New England Journal of Medicine*, *374*, 154–163. http://dx.doi.org/10.1056/NEJMra1508490.

Connecticut General Assembly (2016). Connecticut's seven-day limit on opioid prescriptions. https://www.cga.ct.gov/2016/rpt/pdf/2016-R-0232.pdf

Department of Health and Human Services, & Assistant Secretary for Planning and Evaluation (2015a). Opioid abuse in the U.S. and HHS actions to address opioid-drug related overdoses and death. https://aspe.hhs.gov/basic-report/opioid-abuse-us-and-hhs-actions-address-opioid-drug-related-overdoses-and-deaths

Ling, W., Mooney, L., & Hillhouse, M. (2011). Prescription opioid abuse, pain and addiction: Clinical issues and implications. *Drug and Alcohol Review*, *30*, 300–305. http://dx.doi.org/10.1111/j.1465-3362.2010.00271.x.

Meara, E., Horwitz, J. R., Powell, W., McClelland, L., Weiping, Z., O'Malley, A. J., ... Zhou, W. (2016). State legal restrictions and prescription-opioid use among disabled adults. *New England Journal of Medicine*, *375*, 44–53. http://dx.doi.org/10.1056/NEJMsa1514387.

Muhuri, P. K., Gfroerer, J. G., & Davies, M. C. (2013). Associations of nonmedical pain reliever use and initiation of heroin use in the United States. http://www.samhsa.gov/data/sites/default/files/DR006/DR006/nonmedical-pain-reliever-use-2013.htm

Naeger, S., Ali, M. M., Mutter, R., Mark, T., & Hughey, L. (2016b). Post-discharge prescription fills following an opioid hospitalization. *Psychiatric Services*, *67*, 1262–1264.

Naeger, S., Ali, M. M., Mutter, R., Mark, T., & Hughey, L. (2016a). Post-discharge treatment engagement among patients with an opioid use disorder. *Journal of Substance Abuse Treatment*, *69*, 64–71.

National Alliance for Model State Drug Laws (2014a). Pain management and prescribing practices. http://www.namsdl.org/pain-management-information.cfm

National Alliance for Model State Drug Laws (2014b). PDMP dates of operation. http://www.namsdl.org/library/580225E9-E469-AFA9-50E7579C1D738E71/

National Alliance for Model State Drug Laws (2014c). Prescription monitoring programs – state law and policy profiles. http://www.namsdl.org/library/2155A1A5-BAEF-E751-709EAA09D57E8FDD/

Owens, P. L., Barrett, M. L., Weiss, A. J., Washington, R. E., & Kronick, R. (2014). Hospital inpatient utilization related to opioid overuse among adults, 1993–2012: Statistical brief #177. *Healthcare cost and utilization project (HCUP) statistical briefs*. Rockville, MD: Agency for Healthcare Research and Quality.

Patrick, S. W., Fry, C. E., Jones, T. F., & Buntin, M. B. (2016). Implementation of prescription drug monitoring programs associated with reductions in opioid-related death rates. *Health Affairs (Project Hope)*, *35*, 1324–1332. http://dx.doi.org/10.1377/hlthaff.2015.1496.

Prescription Drug Monitoring Program Training and Technical Assistance Center (2016l). PDMP legislation and operational dates. http://www.pdmpassist.org/content/pdmp-legislation-operational-dates?order=field_state_territory_district_value&sort=asc

Rudd, R. A., Aleshire, N., Zibbell, J. E., & Gladden, R. M. (2016). Increases in drug and opioid overdose deaths–United States, 2000–2014. *MMWR: Morbidity and Mortality Weekly Report*, *64*, 1378–1382. http://dx.doi.org/10.15585/mmwr.mm6450a3.

Simeone, R. (2014). Doctor shopping behavior and the diversion of opioid analgesics: 2008–2012. https://www.whitehouse.gov/sites/default/files/ondcp/policy-and-research/opioid_diversion_08142014.final_.pdf

Substance Abuse and Mental Health Services Administration (2015,). *Results from the 2014 National Survey on Drug Use and Health*. Rockville, MD: Substance Abuse and Mental Health Services Administration.

The White House (2016). Obama administration takes more actions to address the prescription opioid and heroin epidemic. https://www.whitehouse.gov/the-press-office/2016/07/05/obama-administration-takes-more-actions-address-prescription-opioid-and