Race, Gender, and Opioid Treatment Admissions: The Effect of PDMPs on the Most Afflicted

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Abstract

Opioid abuse has been nationally recognized as an epidemic. In an effort to reduce the rapid increase in prescription opioid abuse, diversion, and mortality, state governments have enacted Prescription Drug Monitoring Programs (PDMP) to track all prescribing and dispensing data. In theory PDMPs should detect misuse and improper prescribing of opioids prior to addiction. The opioid epidemic has disproportionately affected some demographic groups more than others [Case & Deaton, 2015]; however, research on demographic differences resulting from targeted opioid-reduction policies are seldom examined. This paper uses a difference-in-differences approach to estimate the effect of PDMP implementation on admissions into drug treatment facilities for opioid abuse across race, gender, and ethnicity. We find that the implementation of PDMPs significantly decreased the probability of admission into a substance abuse treatment facility for opioid abuse. This finding is not consistent across racial or ethnic lines, and is overwhelmingly driven by White individuals, particularly White women.

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I Introduction

In 2014, drug-related deaths claimed roughly 207,000 lives worldwide, and opioid overdose deaths accounted for 69,000 of them [UN, 2016]. In the same year the United States (U.S.) reported 47,055 deaths marking the most recorded in any given year in U.S. history [CDC, 2016]. While opioid abuse is of grave concern worldwide, it has affected U.S. disproportionately, and thus garnered substantial attention among policy makers – particularly, the recent increase in prescription drug abuse. Since 1999, the number of overdose deaths involving prescription opioids has more than quadrupled, although the amount of pain reported by Americans has remained relatively constant [CDC, 2016; Daubresse et al., 2013]. To put this in perspective, during this time there were approximately one-and-a-half times more fatal drug overdoses than deaths from motor vehicle crashes [Rudd et al., 2016].

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Case & Deaton [2015], find that between the years 1993 and 2013 White non-Hispanics (men and women) were the only racial or ethnic group to experience an increase in overall mortality rates – nearly three to four times that of Hispanics and Blacks. An increase attributed, in part, to drug poisonings. It is becoming increasingly clear that the opioid epidemic has a unique racial and gender component. Hollingsworth, Ruhm & Simon [2017] find that negative economic shocks increase overall drug death rates; a result that is driven by opioid deaths among Whites. Additionally, between 1999 and 2010 the CDC found that the U.S. death rate for prescription opioids rose by 400 percent for women, irregardless of race, compared to 237 percent for men.

In addition to the poignancy of drug-related mortality, addiction has a widespread economic impact throughout the country. Drug abuse is associated with higher rates of crime, decreased labor force participation, and lower productivity [Goldstein et al., 1989]. Unexplained decreases in labor force participation among women can possibly be attributed to the effects of the opioid epidemic [Case & Deaton, 2015]. A study prepared for Office of National Drug Control Policy estimated the cost of drug abuse in the United States in 2002 to be $180.8 billion; an estimate that includes resources used to address health, crime, public safety and loss in workforce productivity [NIDA, 2015]. In relation to the drug abuse epidemic, governments typically respond in one of three manners: prevention, law enforcement, and/or treatment. We focus on the seldom researched treatment aspect of the opioid epidemic. The U.S. spends roughly $12 billion on the latter, in the form of drug abuse education and interventions, which include treatment and rehabilitation.[1]

Thus far, the bulk of research on the opioid epidemic has focused on overdoses, over-prescribing, doctor shopping and pill mills. This paper addresses an aspect of the epidemic which has been researched less frequently, the treatment of opioid abuse. We focus on the effects of an increasingly popular prevention/treatment state-run electronic databases used to track and monitor the prescribing and dispensing of controlled prescription drugs – Prescription Drug Monitoring Programs (PDMP). Specifically, we use a difference-in-differences (DD) approach to estimate the effects of PDMPs on the probability that an individual's admission into a drug treatment facility is for prescription opioid abuse. An integral component to examining the effectiveness of a policy is **understanding the key audience**, which we believe is a deficit in the existing literature. The bulk of our analysis focuses on the racial and gender element of the opioid epidemic. Our results suggest that, on average, admissions for opioid abuse into drug treatment facilities is about 1.7 percent lower in PDMP states after implementation. Notably, this finding is driven by White individuals (-2.26 percent) and in particular White women (-2.56 percent). Our results indicate that state PDMPs reduce the number of White male and female opioid treatment admissions– the very population

[1] http://www.drugwarfacts.org/cms/Economics#sthash.amYgq7TK.dpbs.

suffering most from the current opioid epidemic. This result holds true across age groups, referral type, as well as for individuals with private health insurance.

The paper proceeds as follows: Section 2 discusses PDMPs and the opioid epidemic in general. Section 3 describes the data and methods. Section 4 investigates the probability of admissions given the presence of a PDMP. Finally, Section 5 concludes.

II Background

A Prescription Drug Monitoring Programs

The overall goal of PDMPs are to provide health officials with a more complete prescription history in an effort to help reduce the number of individuals that misuse, abuse and/or overdose from Schedule II, III and IV controlled substances.[2] As early as 1930's state law enforcement and regulators were interested in creating a system that would efficiently track and monitor drugs being prescribed/dispensed. The initial uptake of such systems was minimal, with California being the first to adopt a monitoring program in 1939, and only a total of ten states with a similar program by 1992. During this time, a state's PDMP would issue a *script* on which a physician then prescribes a medication and keeps a copy of the prescription. The patient was then to bring two copies of the prescription to the pharmacy. The pharmacy then dispenses the medication, keeps an original copy of the prescription and then forwards a third copy of the prescription to the state (via fax); the state PDMP then enters the information into a database. If needed, reports were then provided to law enforcement and regulatory/licensing agencies. It is evident that this antiquated process can only be made more efficient with the onset of computers.

Although a couple of states did require the electronic transmission and storing of data during the 1990s, Nevada marked a new era, in 2001, by implementing an online system for reporting that provided data to prescribers and pharmacists. In the 1990s, access to patient histories was markedly more difficult and thus queries of prescription history was seldom. During this period, PDMPs focused their attention on forgery and theft at the patient level. Agencies were concerned with prescription pad theft and patients forging prescriptions which were hand-written. This is in stark contrast to current concerns of rampant doctor shopping, where a patient visits multiple prescribers to obtain multiple prescriptions for otherwise illegal drugs. Given advancements in technology and changes in prescriptions policies, forgery has become less of a concern. This may be why studies of the early 2000s provide little evidence on the efficacy of PDMPs [Haffajee, Jena & Weiner, 2015; Paulozzi, Kilbourne & Desai, 2011]. More recently, states have adopted advance computerized data-

[2] Currently, 49 states have a fully functioning PDMP or have implemented legislation to do so. More information can be found at http://www.pdmpassist.org/.

driven approach to collect, track, and analyze prescribing and dispensing information submitted by pharmacists and dispensing practitioners. The data is stored electronically and accessible to health care providers and pharmacist for patients currently under their care. In theory, the implementation of such programs could facilitate the appropriate use of controlled substances, detect and divert abuse of controlled substances, and aid with the intervention of addicted individuals.

In 2001, the federal government acknowledged the need for support for states wishing to adopt PDMPs and aid existing PDMPs to become more comprehensive and practical. These efforts were realized with the Harold Rogers Prescription Drug Monitoring Grants, which awarded approximately $62 million to forty-nine states between the years 2002 to 2010 (U.S. Department of Justice Drug Enforcement Administration) and currently continue to award grants. Given the stark contrast in data collection before and after the 2000's, in conjunction with federal funds provided to enhance monitoring programs, we partition our initial analysis by these time periods. This component of our analysis is novel in practice but not in thought. The distinction in the practicality of PDMPs was motivated by the PDMP Training and Technical Assistance Center at Brandeis University [PDMP Center Excellence, 2017]. The first period, extended from the years 1993 to 2000 (henceforth, the pre-modern era) where six states implemented a PDMP but technological constraints limited the sophistication of the programs. We posit that the second time period beginning in 2000 (henceforth, the modern era), is when PDMPs experience computational advancements in conjunction with increased federal interest in the form of pecuniary contributions.

Previous PDMP studies have looked at health outcomes, provider behavior, and patient behavior. Initial studies on mortality show little to no reduction in overdose deaths as a result of a PDMP implementation [Paulozzi, Kilbourne & Desai, 2011; Li et al., 2014; Meara, Horwitz & Powell, 2016]. Conversely, Bao et al. [2016] use data from the National Ambulatory Medical Care Survey and find that implementation of a PDMP was associated with significant drop in the rate of Schedule II opioid prescribing. More recent evidence suggests that states with stronger PDMPs experience a decrease in opioid-related overdose deaths [Patrick et al., 2016; Pardo, 2017]. On the prescriber side, recent studies find PDMP laws, particularly stricter ones, lead to decreases in the prescribing of opioids. Using Medicare Part D provider data, Alice Ellyson, Jevay Grooms & Alberto Ortega [2017] find that decreases in opioid prescribing is driven by not only PDMP implementation, but by prescriber specialty. Regarding patient behavior, Buchmueller & Carey [2017] find a substantial decrease in misuse (or "doctor shopping") among Medicare Part D beneficiaries in PDMP mandated states. Hefei Wen, Bruce R. Schackman, Brandon Aden & Yuhua Bao [2017] examine opioid prescriptions received by Medicaid enrollees and find a large reduction in prescriptions to this population as a result of a PDMP.

B Opioid Epidemic

Albeit growing, the PDMP literature seldom considers the effect of PDMPs on admissions into substance abuse treatment facilities. In 2008, the CDC estimated that for every prescription drug death, 10 individuals sought substance abuse treatment. Although our analysis does not explicitly measure rates of opioid use, individuals checking into treatment facilities serve as a good proxy. It is also of policy relevance to examine the effect state-level policies have on scarce resources, such as drug treatment facilities. Moreover, studies that consider differential impacts of the opioid epidemic across race and/or gender as a result of policy implementation are scarce. This is surprising, given the differences in opioid abuse across demographics. Unlike drug epidemic trends of the past, minority populations have experienced a less dramatic increase in drug addiction and deaths from the opioids relative to White adults [Hedegaard, Warner & Miniño, 2017].

Recent literature has deemed the opioid epidemic as one which impacts White America at a higher rate, but little to no attention has focused on gender. Women have the greatest risk for opioid abuse, as they experience chronic pain more frequently and are prescribed pain medication at higher rates then men [CDC, 2013]. While overdose deaths from prescription opioids is greatest among men, from 1993 to 2010 women were hospitalized at higher rates for prescription drug overdoses than men [CDC, 2016]. Considering the effects of the opioid epidemic on women it is also of grave concern when considering its adverse effects on pregnant women. In the sample we consider, roughly one in four pregnant women which entered treatment for substance abuse, entered for a non-heroin opioid substances. Between 2000 and 2009, opioid use among women who gave birth increased in the U.S. from 1.19 to 5.63 per 1,000 births per year [Smith & Lipari, 2017].

Thus, we contribute to the PDMP literature by not only examining opioid admission differences across PDMP implementation periods, but by also considering the differential effects this program may have across race and gender. In theory, given that prescribers are more readily able to track patients' past prescription details, states with PDMPs should expect fewer opioid abusers relative to the natural trend. If this holds, then states that implement PDMPs can more adequately detect abuse and misuse, and therefore experience lower prescription opioid admissions into substance treatment facilities.

III Data & Methods

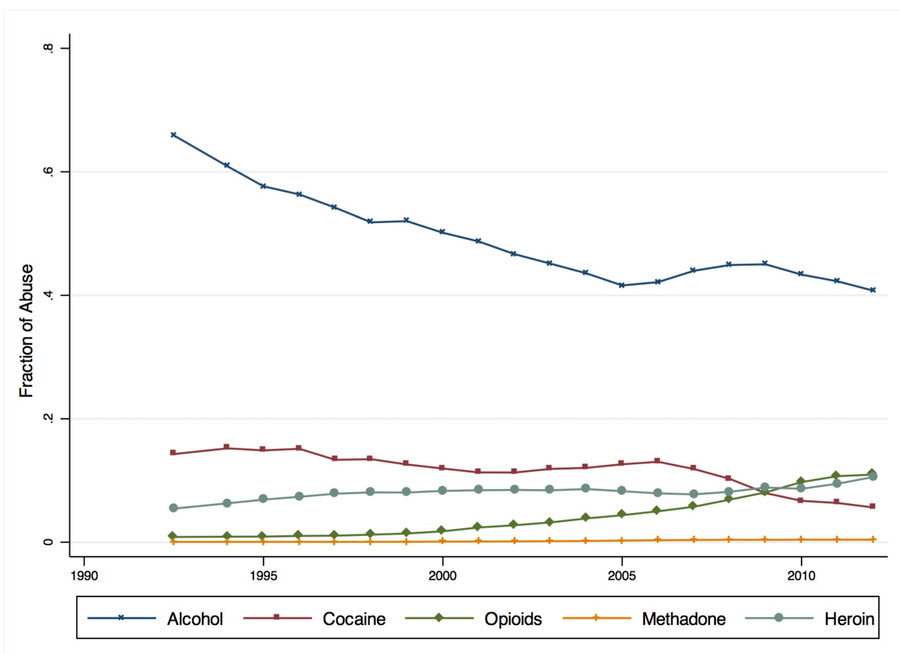
To conduct the analysis, data is collected from a variety of sources. Details on the characteristics of each state's PDMP originates from Prescription Drug Monitoring Program Training and Technical Assistance Center (PDMP TTAC) at Brandeis University. For ease of understanding, in the

Appendix we provide a table of the states used in our analysis with specific PDMP information including operational dates. PDMPs vary in the schedule of drugs they track, ranging from Schedule II to V or II to IV. For the purpose of this paper we are only interested in opioids which are generally Scheduled II. State demographic data is collected from The Correlates of State Policy Project at Michigan State University [Jordan & Grossmann, 2016].

A Substance Abuse Admissions Data

Data on public substance abuse treatment centers, Treatment Episode Data Set –Admissions (TEDS), originates from the Substance Abuse and Mental Health Service Administration (SAMHSA) (ICPSR 25221). TEDS is a national census data system of annual admissions to substance abuse treatment facilities. The data set tracks admissions from years 1992 to 2012 and comprises of over 37 million observations. It also contains many individual level characteristics collected at admission into treatment. A substantial benefit of this data set is that the information collected on admissions is standardized across all years. A limitation of the data is that admissions are not unique to a patient; we cannot track whether the same client experiences multiple admissions during our sample period.[3] While we are unable to follow individuals, we are capable of identifying the number of prior admissions they have had for substance abuse; we later utilize this information to perform sensitivity analysis.

Figure 1: **Treatment Admission Trends in the U.S. 1992 - 2012**



TEDS contains 67 percent of the entire population of treatment admissions to all known providers

[3]Admissions accounts for each initial admission and individuals who transfer facilities are not included.

[Dave & Mukerjee, 2011]. Over 90 percent of all treatment centers that receive any government funding (federal block grants, Medicaid, Medicare, or Tricare) are required to report admissions data annually on all admissions regardless of insurance type. Figure 1 illustrates the national trend of admissions into treatment across several substances. On average, alcohol abuse is declining, and accounts for the highest number of admissions across all years. During this same time, admissions for opioids and heroin abuse appear to have risen.

Table 1 provides counts on admissions for opioid and non-opioid abuse by year, race, ethnicity and gender for the states considered in our analysis. On average, and across all substances, those who identify as White are under-represented in substance abuse admissions relative to the U.S. population. Conversely those who identify as Black are over-represented, and those who identify as Hispanic are equally represented. In the 2005, the National Survey on Drug Use and Health [HHS, 2006] estimated that individuals who identify as American Indian or Alaskan Natives (12.8 percent) and Black (9.7 percent) were the only race or ethnicity that used illicit drugs at a higher rate than individuals who identify as White (8.1 percent). In Table 1, Black opioid abuse admissions accounts for 4.8 percent of all opioid admissions, and Hispanic opioid admissions account for about 4.1 percent of all opioid admissions. White opioid abuse admissions account for 90 percent of all opioid admissions in our data; this is about 10.6 percent of all substance abuse admissions for White individuals. While the percents cited all refer to our sample, they mirror that of the U.S. population of treatment admissions (as reported by TEDS).

As illustrated in Figure 2, traditionally, in the U.S., men account for the vast majority of substance users who seek treatment. If we **exclude opioids**, our sample indicates that men account for 68.2 percent of all substance abuse admissions. Yet, on average, women abuse prescription opioids at nearly the same rate as men, 45 percent and 55 percent, respectively. In our sample, 10.5 percent of total female admissions are for opioid abuse, compared to 6.1 percent of total male admission are for opioid abuse. Given that the opioid epidemic has been widely accepted as an issue which more heavily affects White America, we stratify our results by race, ethnicity and gender to investigate whether PDMP implementation results in disproportionate effects among different groups.

While data is readily available for earlier years, our analysis will focus on the modern era of PDMP implementation. Our first set of regressions uses all years (1992-2012) and partitions the eras (pre and post-modern) to illustrate the contrasting effects. In an effort to narrow the scope of our analysis to the current epidemic, subsequent analysis focuses on the years 2000 to 2012. Utilizing years prior to 2000 could affect the pre-treatment estimate and distort the effect of PDMPs on treatment admissions, particularly given the aforementioned differences across eras.

Opioid abuse is categorized as any individual who entered treatment with prescription opioids

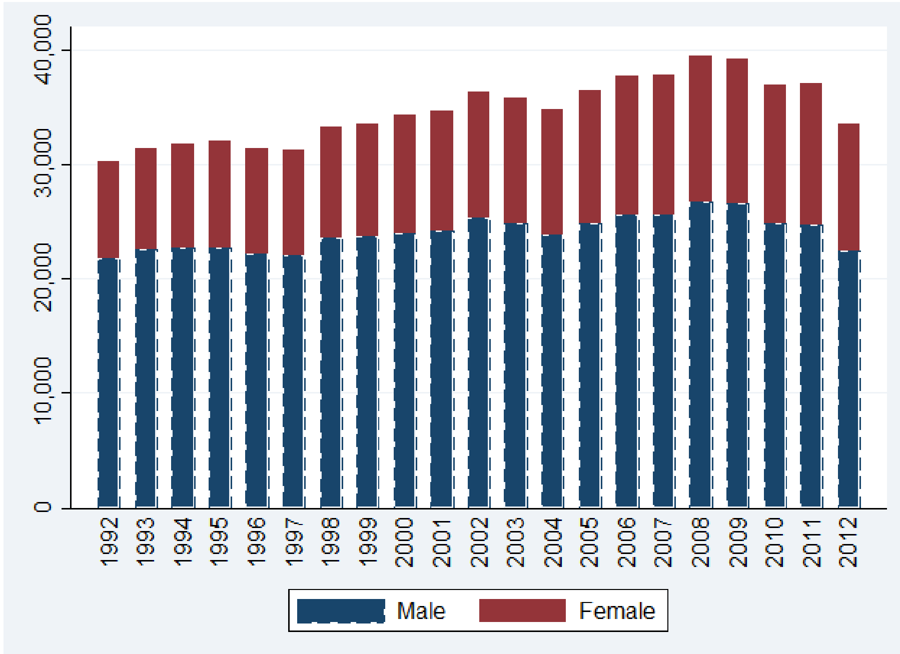
Table 1: **Demographics of Treatment Admissions**

Year		Opiod Admissions	Non-Opioid Admissions	Total Admissions
	2000	42,545	1,707,182	1,749,727
	2001	57,341	1,711,487	1,768,828
	2002	70,408	1,817,582	1,887,990
	2003	79,491	1,785,624	1,865,115
	2004	90,650	1,717,327	1,807,977
	2005	105,261	1,790,089	1,895,350
	2006	123,569	1,836,375	1,959,944
	2007	143,575	1,821,620	1,965,195
	2008	176,082	1,878,917	2,054,999
	2009	206,294	1,832,173	2,038,467
	2010	234,165	1,691,182	1,925,347
	2011	267,999	1,660,677	1,928,676
	2012	243,205	1,506,565	1,749,770
Race				
	Black	81,418	5,428,183	5,509,601
	White	1,638,573	13,842,892	15,481,465
Ethnicity				
	Hispanic	72,089	2,939,498	3,011,587
	Non-Hispanic	1,694,371	18,761,894	20,456,265
Gender				
	Female	824,494	6,990,029	7,814,523
	Male	1,015,749	15,748,196	16,763,945

as the primary or secondary substance of abuse. Substance of abuse does not include all drugs which might have been used by an individual, but rather the drug primarily responsible for treatment admission. Opioid abuse poses a fatal risk whether abused in singularity or with additional substances. Opioids can cause respiratory depression and have a higher risk of overdose when used in combination with alcohol and/or sedative medication [CDC, 2016].

It is important to note that admissions where marijuana is the primary source of substance abuse, along with admissions which do not identify a type of substance abuse are dropped from our analysis. As of 2016, marijuana has been legalized for medical use in 26 states and the District of Colombia. National attitudes toward marijuana have evolved, and although treatment admissions for marijuana may be identified as abuse, they may simply indicate use. While marijuana is legal for recreational use in some states, it is still deemed federally illegal and thus not every employer recognizes marijuana as a recreational/legal drug, even when states implement legislation declaring marijuana as such. Therefore dropping marijuana for our analysis allows us to circumvent the vague legality and unclear definition of when to classify marijuana as abuse.

Figure 2: **Substance Abuse Admissions by Gender (TEDS 1992 - 2012)**



B Empirical Strategy

The difference in timing in which states enacted a PDMP provides a natural experiment for which we are able to estimate the effects on admissions into treatment centers for opioid abuse. To estimate the policy effect on admissions we use the aforementioned DD approach. States are considered “treated" if they had an operational PDMP prior to 2012. Our analysis focuses on states that implemented a PDMP during the modern era, (2000 to 2012).[4] The control group consists of states which did not implement a PDMP for the entirety of our analysis, and thus did not have a functioning PDMP in place prior to 2012.[5] Control and treatment groups for both modern era and pre-modern era are identified in Figure 3. The data for our main specification consists of over 20 million admissions, where an admission is not followed throughout the length of our study, rather each admission represent a unique observation.

In our preferred specification, we estimate the effect of PDMP adoption on the probability of an admission for opioid abuse relative to admission for all other substances by using

$$Y_{igt} = \psi_t + \eta_g + X_{gt}\beta + Z_{igt}\gamma_{gt} + u_{igt} \tag{1}$$

Where Y_{igt} is the dependent variable for individual i, in (treatment/control) group g, in year t.

[4]Commonly referred as the treatment group: AL, AK, AZ, CO, CT, FL, IA, KS, LA, ME, MN, MS, NE, NJ, NM, NC, ND, OH, OR, SC, SD, TN, VA, VT, WA, WY

[5]Control group for all analysis: AR, GA, MD, MO, NH.

Table 2: **Individual and State Variables**

Individual	**Description**
Substance 1	Primary substance of abuse as identified by patient at time of admission
Substance 2	Secondary substance of abuse as identified by patient at time of admission
Year	Year of admission into treatment (1993 - 2012)
Age	Age at time of admission, categorical and ranges from 12 to over 55)
Gender	Sex
Race	Alaskan Native, American Indian, Asian, Black, White, or Other
Hispanic	If of any Hispanic origin; Puerto Rican, Mexican, Cuban, Other
Married	Marital status
HS Educ	High school educated
Employment	Employment at time of admission; full time, part time, unemployed, not in labor force
Veteran	Veteran or not
Living Arrange	Living arrangement; independent, dependent, homeless
State	States are identified using fipscodes
Wait	Days waited to receive treatment
Primary Source	Referral Source; self, criminal, community organization, health professional, employer
Health Ins	Type of health insurance; private, medicaid, medicare/tricare, none
State Level	
lnPop	Natural log of population
Unemployment	Unemployment rate
Workers Comp	Worker's compensation
Income	Income per capita
Educ Spend	Education spending per capita
Health Spend	Health care spending per capita
Poverty Rate	Poverty rate per state per given year

The ψ_t term controls for time trends, η_g are (treatment/control) group effects, X_{gt} is our policy variable of interest and determines if a state has implemented a PDMP in year t. Z_{igt} are observed covariates at individual and state level, and u_{igt} is our error term. β is our coefficient of interest and measures the probability of checking into a substance abuse facility for opioid abuse relative to other substances. Admissions are reported at the individual level (i) allowing us to control for individual level characteristics.

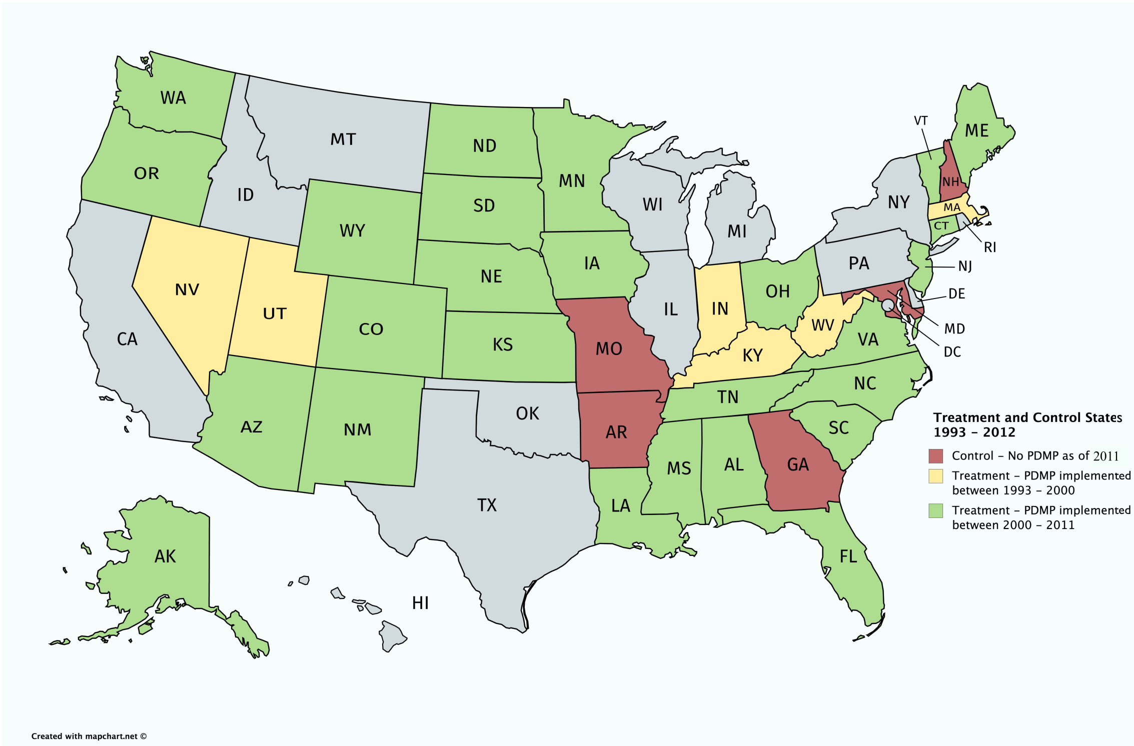
Note that Y_{igt} is binary and takes the value of 1 if an individual is admitted into treatment for opioid abuse and zero otherwise

$$Y_{gt} = \begin{cases} 1, & \text{if Primary or secondary substance is a (prescription) opioid} \\ 0, & \text{if Primary no r secondary substance is not a (prescription) opioid} \end{cases} \tag{2}$$

Thus we employ a bivariate response (probit) model to estimate the probability of an admission for opioid abuse as a result of PDMP implementation, as shown in equation (3)

$$Pr(y=1|g,t) = \Phi(\psi_t + \eta_g + X_{gt}\beta + Z_{igt}\gamma_{gt} + u_{igt}), \quad 0 < \Phi < 1 \tag{3}$$

Figure 3: **Control and Treatment States between 1993 and 2012**



As mentioned, the time trend is estimated using ψ_t. Additionally, we consider year binaries in separate specifications to ensure robustness of our results. The set of individual and demographic controls used are listed and described in the aforementioned Table 2. We also relax the linearity assumption of equation (1) and demonstrate that our results are robust to using a linear probability model. All results reported in the following section are in marginal effects of the probit model. As discussed in Chunrong & Norton [2003], coefficients of an interaction term for a non-linear model can be obsolete, the magnitude and directional effect of the statistically significant variable can lead to incoherent interpretation unless transformed.

Moreover, as previously mentioned, we lack facility identifiers, which prohibits us from aggregating admissions to the facility level; thus we are unable to use a the total number of admissions into a facility (i.e. a continuous dependent variable). However, we do run our analysis by aggregating admissions at the state level; these results are by and large insignificant and reported in the Appendix. We do not focus on this specification because aggregating at the state level inhibits our ability to exploit the richness of the TEDs data. Using a state measure prevents us from controlling for many observables offering insight into mitigating factors that may augment the effectiveness of PDMPs. In addition, studies that do consider TED's admissions data at the state level normalize by population, which inherently underestimates the number of individuals entering treatment within a state. Our aggregate results are consistent with the findings of two working papers examining different components of PDMPs and aggregate measures of TEDs data [Dave, Grecu & Saffer, 2017] and [Birk & Waddell, 2017]. Our individual level estimates indicate that aggregating TEDs data may be underestimating the efficacy of PDMPs.

There may also be a question as to whether our baseline results are driven by individuals with prior treatment admissions. Over 50 percent of admissions are reported as having no prior admissions for the treatment of substance abuse, and roughly 20 percent report having had only one prior treatment episode. As a sensitivity check we run three separate analysis where we restrict the data to individuals with no prior admissions, 1 or fewer admissions, and more than 5 prior admissions, respectively. Results from all three specifications are significant and have the same directional effect as our baseline specifications.

IV Probability of Admission

First, to validate our *modern* and *pre-modern* era assumptions of PDMP implementation we run preliminary analysis using both time frames to estimate their impact on admissions into treatment facilities for opioid abuse. We also report the linear probability model (LPM) estimates to verify our use of the probit model. As reported in Table 3, the treatment effect is significant and negative during the modern era (2000-2012) for both the LPM and probit models, and insignificant during the pre-modern era, as previously hypothesized. Thus, all subsequent analysis use a probit model and focuses on the modern era, all the treatment effects are for PDMPs implemented between 2000 and 2012.

Recalling that we report marginal effects, results in Table 3 column 2, indicate that on average individuals entering treatment for prescription opioid abuse is about 1.77 percent lower once a state implements a PDMP relative to states which did not have a PDMP during the modern era. On average, this is equivalent to 668 fewer treatment admissions per year for opioid abuse during post-implementation years.[6] It is estimated that, on average and across all treatment and control states, admissions for opioid abuse increased by 1.5 percent with each additional year, this holds with the existing literature. Furthermore, White individuals are 7.5 percent more likely to enter treatment for opioid abuse than any other race. The gender binary, in Table 3, suggests that men, are 3.9 percent less likely to be admitted for opioid and admissions. Moreover, individuals between 21 and 29 years of age are between 6.5 and 7.2 percent more likely be admitted for opioid abuse.

A concern may be that the adoption of a fully functioning electronic database did not occur immediately in 2000, as a robustness check we allow for the modern era to begin in 2001, 2002, 2003 and 2004. Our variable of interest is similar in magnitude, has the same directional effect, and is

[6] Number of admissions is calculated using Table 12 in the Appendix.

Table 3: **Admission for Opioid Abuse**

Treatment: PDMP States - Pre-modern & Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) LPM 2000-2012	(2) Probit ME 2000-2012	(3) Probit ME 1993 - 2000
Time Trend	0.0175***	0.0145***	0.00207***
	(0.00203)	(0.00130)	(0.000427)
PDMP	0.0304***	0.0201***	0.0155***
	(0.00884)	(0.00619)	(0.00134)
PDMP * Policy Year	-0.0242**	-0.0177**	0.000876
	(0.0122)	(0.00872)	(0.00423)
Male	-0.0444***	-0.0385***	-0.00986***
	(0.00262)	(0.00199)	(0.00235)
White	0.0806***	0.0753***	0.0162***
	(0.00691)	(0.00610)	(0.00100)
Age (18-20)	0.0297***	0.0335***	-0.00634***
	(0.00338)	(0.00416)	(0.00206)
Age (21-24)	0.0636***	0.0658***	-0.00278
	(0.00538)	(0.00539)	(0.00199)
Age (25-29)	0.0720***	0.0722***	0.000189
	(0.00541)	(0.00530)	(0.00147)
Age (30-34)	0.0525***	0.0550***	0.00190
	(0.00395)	(0.00417)	(0.00217)
Age (35-39)	0.0247***	0.0264***	0.00573**
	(0.00239)	(0.00280)	(0.00231)
HS Education	0.0158***	0.0129***	0.00631***
	(0.00237)	(0.00174)	(0.000288)
Veteran	-0.0108***	-0.0119***	-0.00409***
	(0.00380)	(0.00322)	(0.000677)
ln(Population)	0.0342***	0.0283***	0.00617***
	(0.00684)	(0.00530)	(0.00130)
Income Per Capita	-1.38e-06*	-9.16e-07	-6.25e-07*
	(8.14e-07)	(6.65e-07)	(3.75e-07)
Constant	-0.530***	-	-
	(0.106)	-	-
Observations	5,449,446	5,449,446	1,267,516
Cluster MSA	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

statistically significant for all of these years. Moreover, as falsification checks, we examine the effect of PDMPs on alcohol and heroin admissions at the individual level– these results are insignificant and reported in the Apokpendix.

A Race and Gender Analysis

In Table 4, we stratify by race and gender. Coinciding with prior literature, we find the treatment effect is concentrated among individuals who identify as White. PDMP states experience a 2.26 percent decreased in the number of White individuals entering treatment for opioid abuse. For individuals who identify as Hispanic we observe less than a 1-percent decrease and an insignificant difference in individuals who identify as Black. In columns 1 and 2, of Table 4, the analysis is stratified by gender. The implementation of PDMPs in the treatment states accounts for a 2.7 and 1.4 percent decreases in individuals entering treatment for opioid abuse among female and male admissions, respectively.

In Table 5, results for opioid admissions stratified by race/ethnicity and gender are reported. When restricting the analysis to only White individuals, we see that after PDMP implementation there is a 1.6 percent decrease in White male admissions for opioid abuse relative to non-PDMP states; the decrease is 2.6 percent when restricting our analysis to White women. On average, this is equivalent to 295 fewer admissions per year into to treatment for opioid abuse for men, and about 404 fewer admissions for women during post-implementation years. For Black men and women, and Hispanic men and women the treatment effect are insignificant or economically inconsequential.

As illustrated in Table 3 - 5, age plays a role in treatment admissions. To investigate whether this effect disproportionately differs among PDMP and non-PDMP states, the data is split into three age groups; 18 to 29, 30 to 44, and 45 and over. In Table 6, we do not observe large variations across age groups and find our estimates are significant and consistent with our results thus far. While individuals between 21 and 34 enter treatment for opioid abuse at a relatively higher rate compared to other age groups, we do not observe this group experiencing vastly different effects as a result of a PDMP.

Table 4: **Admission for Opioid Abuse:** Stratified by Gender or Race (Probit ME)

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic
Time Trend	0.0111***	0.0225***	0.0195***	0.00340***	0.00761***
	(0.00115)	(0.00174)	(0.00190)	(0.000290)	(0.000845)
PDMP	0.0124**	0.0379***	0.0212**	0.00864***	-0.00628
	(0.00585)	(0.00788)	(0.00949)	(0.00171)	(0.00672)
PDMP * Policy Year	-0.0137*	-0.0269**	-0.0226*	-0.00289	-0.00901*
	(0.00793)	(0.0108)	(0.0124)	(0.00181)	(0.00521)
Male	-	-	-0.0485***	-0.0118***	-0.0294***
	-	-	(0.00195)	(0.00124)	(0.00263)
White	0.0638***	0.102***	-	-	-
	(0.00591)	(0.00675)	-	-	-
Age (18-20)	0.0350***	0.0273***	0.0473***	-0.00346**	0.0153***
	(0.00406)	(0.00586)	(0.00554)	(0.00135)	(0.00267)
Age (21-24)	0.0636***	0.0690***	0.0902***	0.00162	0.0291***
	(0.00478)	(0.00772)	(0.00704)	(0.00170)	(0.00529)
Age (25-29)	0.0666***	0.0824***	0.0992***	0.00394**	0.0299***
	(0.00483)	(0.00731)	(0.00690)	(0.00165)	(0.00460)
Age (30-34)	0.0488***	0.0656***	0.0769***	0.00256*	0.0201***
	(0.00387)	(0.00580)	(0.00527)	(0.00132)	(0.00336)
Age (35-39)	0.0232***	0.0305***	0.0395***	-0.00233**	0.00962***
	(0.00264)	(0.00389)	(0.00337)	(0.00106)	(0.00227)
HS Education	0.00951***	0.0195***	0.0156***	0.00726***	0.0213***
	(0.00158)	(0.00219)	(0.00249)	(0.000612)	(0.00420)
Veteran	-0.00945***	-0.0109	-0.0173***	-0.00213**	0.000122
	(0.00260)	(0.00719)	(0.00467)	(0.000964)	(0.00252)
ln(Population)	0.0259***	0.0333***	0.0450***	-0.00315**	0.0120**
	(0.00449)	(0.00738)	(0.00752)	(0.00158)	(0.00468)
Income Per Capita	-3.15e-07	-2.48e-06***	-1.44e-06	-3.48e-07***	6.43e-09
	(6.00e-07)	(8.17e-07)	(9.95e-07)	(1.26e-07)	(4.28e-07)
Observations	3,654,223	1,795,223	3,901,303	1,119,643	469,548
Cluster MSA	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table 5: **Admission for Opioid Abuse:** Stratified by Gender and Race (Probit ME)

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) Male White	(2) Female White	(3) Male Black	(4) Female Black	(5) Male Hispanic	(6) Female Hispanic
Time Trend	0.0123***	0.0224***	0.00205***	0.00419***	0.00385***	0.0112***
	(0.00131)	(0.00187)	(0.000204)	(0.000298)	(0.000611)	(0.00108)
PDMP	0.0160**	0.0382***	0.00612***	0.0110***	-0.00633	0.00128
	(0.00762)	(0.00896)	(0.00118)	(0.00200)	(0.00451)	(0.0127)
PDMP * Policy Year	-0.0160*	-0.0256**	-0.00214*	-0.00316	-0.00431	-0.0134*
	(0.00867)	(0.0112)	(0.00112)	(0.00235)	(0.00294)	(0.00690)
Age (18-20)	0.0395***	0.0192***	-0.00245**	-0.00666***	0.0130***	0.00454
	(0.00477)	(0.00624)	(0.00104)	(0.00169)	(0.00222)	(0.00419)
Age (21-24)	0.0728***	0.0677***	0.00213	-0.00287**	0.0210***	0.0251***
	(0.00582)	(0.00809)	(0.00154)	(0.00136)	(0.00384)	(0.00681)
Age (25-29)	0.0785***	0.0845***	0.00234*	0.00220	0.0191***	0.0344***
	(0.00591)	(0.00762)	(0.00138)	(0.00163)	(0.00302)	(0.00757)
Age (30-34)	0.0588***	0.0676***	0.000609	0.000939	0.0131***	0.0240***
	(0.00465)	(0.00570)	(0.00105)	(0.00142)	(0.00236)	(0.00622)
Age (35-39)	0.0315***	0.0349***	-0.00207**	-0.00384***	0.00717***	0.00978**
	(0.00314)	(0.00389)	(0.000864)	(0.00117)	(0.00150)	(0.00466)
HS Education	0.0117***	0.0207***	0.00291***	0.0139***	0.0142***	0.0281***
	(0.00185)	(0.00251)	(0.000413)	(0.00120)	(0.00309)	(0.00458)
Veteran	-0.0126***	-0.0184**	-0.00155***	-0.00230	-0.000351	0.00129
	(0.00292)	(0.00753)	(0.000540)	(0.00214)	(0.00160)	(0.00683)
ln(Population)	0.0326***	0.0428***	-0.00177	-0.00530**	0.00781***	0.0137*
	(0.00535)	(0.00833)	(0.00109)	(0.00213)	(0.00294)	(0.00738)
Income Per Capita	-7.18e-07	-3.34e-06***	-2.16e-07**	-6.07e-07***	2.24e-07	-1.00e-06*
	(8.57e-07)	(1.10e-06)	(9.68e-08)	(1.62e-07)	(2.97e-07)	(5.54e-07)
Observations	3,316,584	1,664,674	1,059,934	452,785	472,554	132,817
Cluster MSA	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: **Admission for Opioid Abuse:** Stratified by Gender and Age (Probit ME)

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) Male 18 - 29	(2) Male 30 - 44	(3) Male over 44	(4) Female 18 - 29	(5) Female 30 - 44	(6) Female over 44
Time Trend	0.00632***	0.00390***	0.00504***	0.0138***	0.00874***	0.00979***
	(0.000769)	(0.000641)	(0.000513)	(0.00105)	(0.000883)	(0.00108)
PDMP	0.0143***	0.0106***	0.00968***	0.0311***	0.0233***	0.0234***
	(0.00383)	(0.00334)	(0.00303)	(0.00533)	(0.00450)	(0.00821)
PDMP * Policy Year	-0.00885*	-0.00977**	-0.0111***	-0.0165**	-0.0146**	-0.0160**
	(0.00506)	(0.00416)	(0.00360)	(0.00703)	(0.00639)	(0.00739)
White	0.0482***	0.0377***	0.0264***	0.0893***	0.0811***	0.0630***
	(0.00540)	(0.00479)	(0.00361)	(0.00576)	(0.00498)	(0.00464)
HS Education	0.00726***	0.00707***	0.00629***	0.0180***	0.00807***	-0.00320
	(0.000868)	(0.00110)	(0.00171)	(0.00139)	(0.00188)	(0.00296)
Veteran	-0.0116***	-0.00844***	-0.00639***	-0.0116**	-0.0112***	-0.0160***
	(0.00143)	(0.00112)	(0.00147)	(0.00512)	(0.00405)	(0.00611)
ln(Population)	0.0183***	0.0164***	0.0157***	0.0197***	0.0188***	0.0190***
	(0.00319)	(0.00263)	(0.00212)	(0.00535)	(0.00409)	(0.00403)
Income Per Capita	-6.87e-07	-3.13e-07	-2.56e-07	-2.48e-06***	-1.63e-06***	-1.90e-06***
	(5.42e-07)	(4.30e-07)	(3.21e-07)	(6.60e-07)	(5.29e-07)	(5.41e-07)
Observations	2,838,750	1,079,954	245,583	1,317,594	395,595	69,468
Cluster MSA	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

B Additional Analysis

B.1 Referral Type

Individual-level admission characteristics grants us the ability to identify confounding factors which could impact the treatment effect. In particular, does referral or insurance type impact the significance or magnitude of the effect. We begin by splitting the universe of referral sources into three categories: (1) self or health, (2) community, and (3) criminal. Less than 3 percent of the sample are missing their referral type. One third of the sample enter treatment upon a self-referral, another one third via a criminal referral. The remaining referrals are from a drug abuse provider (10.9 percent), health care provider (6.0 percent), community referral (9.6 percent), school (1.1 percent), or employer (0.9 percent). For each referral category we further stratify by race and gender. Consistent with prior analysis, results for all races, except White, are insignificant and therefore not reported.

Individuals who enter treatment upon a self-referral are reported in Table 7 and results are congruous with our aforementioned findings, with the strongest effect being amongst female admissions. When restricting to Women who self-refer into a treatment facility, across all races, we see that PDMP implementation results in 3.9 percent fewer opioid admissions. This effect is concentrated among White women– with a the decrease of roughly 4.8 percent (column 6).

Results for health and community referrals are reported in Table 15 in the appendix; the estimates for PDMP implementation are significant and similar across gender. States implementing PDMPs see a 1.7 percent decrease in admissions for opioid abuse for White men and women when compared to non-PDMP states. Results for criminally referred admissions are also reported in Table 16 of the appendix. While the results aren't are as large as those observed in Table 7, the decrease is larger for White women than White men, 1.8 and 0.8 percent, respectively.

Table 7: **Admission for Opioid Abuse by Self-Referral:** Stratified by Race and Gender

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) All Sexes All Races	(2) Male All Races	(3) Women All Races	(4) All Sexes White	(5) Male White	(6) Female White
Time Trend	0.0189***	0.0154***	0.0262***	0.0261***	0.0225***	0.0330***
	(0.00155)	(0.00132)	(0.00210)	(0.00231)	(0.00205)	(0.00288)
PDMP	0.0481***	0.0379***	0.0697***	0.0626***	0.0512***	0.0842***
	(0.00762)	(0.00706)	(0.00966)	(0.0115)	(0.0112)	(0.0128)
PDMP * Policy Year	-0.0270***	-0.0215***	-0.0386***	-0.0374***	-0.0317***	-0.0483***
	(0.00837)	(0.00725)	(0.0110)	(0.0121)	(0.0110)	(0.0145)
Male	-0.0317***	-	-	-0.0408***	-	-
	(0.00250)	-	-	(0.00278)	-	-
White	0.100***	0.0885***	0.124***	-	-	-
	(0.00665)	(0.00624)	(0.00799)	-	-	-
Age (18-20)	0.0775***	0.0805***	0.0692***	0.105***	0.115***	0.0861***
	(0.00790)	(0.00776)	(0.0108)	(0.00982)	(0.0102)	(0.0127)
Age (21-24)	0.114***	0.112***	0.117***	0.152***	0.154***	0.145***
	(0.00942)	(0.00844)	(0.0134)	(0.0114)	(0.0106)	(0.0152)
Age (25-29)	0.106***	0.0993***	0.116***	0.143***	0.140***	0.146***
	(0.00880)	(0.00785)	(0.0124)	(0.0107)	(0.0101)	(0.0138)
Age (30-34)	0.0733***	0.0651***	0.0871***	0.104***	0.0961***	0.115***
	(0.00697)	(0.00620)	(0.00997)	(0.00848)	(0.00807)	(0.0112)
Age (35-39)	0.0347***	0.0291***	0.0443***	0.0546***	0.0479***	0.0645***
	(0.00451)	(0.00403)	(0.00689)	(0.00553)	(0.00544)	(0.00781)
HS Education	0.0103***	0.00916***	0.0119***	0.0108**	0.0110**	0.00933*
	(0.00316)	(0.00285)	(0.00405)	(0.00468)	(0.00444)	(0.00553)
Veteran	-0.0116**	-0.00922**	-0.0110	-0.0170**	-0.0142***	-0.0158
	(0.00496)	(0.00367)	(0.0117)	(0.00707)	(0.00552)	(0.0149)
ln(Population)	0.0273***	0.0255***	0.0304**	0.0446***	0.0420***	0.0491***
	(0.00904)	(0.00784)	(0.0119)	(0.0125)	(0.0114)	(0.0150)
Income Per Capita	-1.71e-06**	-1.08e-06	-3.19e-06***	-2.55e-06**	-1.69e-06*	-4.37e-06***
	(7.36e-07)	(6.56e-07)	(9.30e-07)	(1.08e-06)	(1.00e-06)	(1.25e-06)
Observations	2,117,083	1,386,418	730,665	1,510,319	972,241	538,078
Cluster MSA	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

B.2 Insurance Type

Next, we estimate the admission into treatment for opioid abuse for different insurance types. In Table 8 we observe that regardless of race, PDMP implementation decreases the number of admissions into treatment for opioid abuse by 3.7 percent. A results that is larger in magnitude than those presented for self-referral. This result proves to be somewhat misleading as the treatment effect among those with private insurance is driven by White individuals, about 4.2 percent. Whereas the decrease for Blacks is 0.7 percent and Hispanics is 1.2 percent. Table 9 investigates these effects across gender. States implementing a PDMP experience a 5.3 percent decrease in the number of

Table 8: **Admission for Opioid Abuse by Private Insurance:** Stratified by Race

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) All Races	(2) White	(3) Black	(4) Hispanic
Time Trend	0.0105***	0.0117***	0.00285***	0.00426***
	(0.00123)	(0.00141)	(0.000419)	(0.000931)
PDMP	-0.0307**	-0.0382**	0.00316*	-0.0203
	(0.0146)	(0.0159)	(0.00181)	(0.0152)
PDMP * Policy Year	-0.0372***	-0.0419***	-0.00670***	-0.0124***
	(0.00954)	(0.0108)	(0.00247)	(0.00382)
Male	-0.0340***	-0.0363***	-0.0143***	-0.0267***
	(0.00523)	(0.00543)	(0.00390)	(0.00606)
Age (18-20)	0.0403***	0.0426***	-0.00103	0.00672
	(0.0122)	(0.0137)	(0.00230)	(0.00757)
Age (21-24)	0.0467***	0.0506**	0.00142	0.00746
	(0.0179)	(0.0199)	(0.00328)	(0.00855)
Age (25-29)	0.0414***	0.0475***	-0.00226*	0.00832
	(0.0146)	(0.0172)	(0.00125)	(0.00847)
Age (30-34)	0.0389***	0.0459***	0.000738	0.00912
	(0.0117)	(0.0139)	(0.00183)	(0.00786)
Age (35-39)	0.0205***	0.0255***	-0.00138	0.00186
	(0.00670)	(0.00828)	(0.00148)	(0.00340)
HS Education	0.0121***	0.00998**	0.00680***	0.0115**
	(0.00401)	(0.00454)	(0.00132)	(0.00517)
Veteran	-0.0168***	-0.0184***	-0.00164	-0.00183
	(0.00205)	(0.00210)	(0.00162)	(0.00306)
ln(Population)	0.0204***	0.0288***	0.00311	0.00981
	(0.00669)	(0.00814)	(0.00414)	(0.00599)
Income Per Capita	2.25e-06***	2.24e-06**	5.89e-08	6.15e-07
	(8.60e-07)	(9.80e-07)	(2.25e-07)	(5.12e-07)
Observations	421,537	356,386	42,831	48,319
Cluster MSA	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

White women entering treatment for opioid abuse. The decrease for White men residing in PDMP states is significant and slightly smaller, 3.7 percent.

We also perform similar analysis on individuals who have Medicaid, Medicare/Tricare, and no insurance separately and find no significant effects. While these results are interesting, they are mostly speculative as data on insurance type is one of the few variables which were not widely reported in TEDS. More than 50 percent of the sample listed insurance type as unknown, 27 percent report no insurance and less than 6 percent of the sample reported having private insurance. More research on the role of insurance type and drug abuse treatment could prove beneficial in better understanding of not only the opioid epidemic, but also mental health treatment.

Table 9: **Admission for Opioid Abuse by Private Insurance:** Stratified by Race and Gender

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) Male All Races	(2) Female All Races	(3) All Sexes White	(4) Male White	(5) Female White
Time Trend	0.00878***	0.0151***	0.0117***	0.0102***	0.0154***
	(0.00119)	(0.00154)	(0.00141)	(0.00142)	(0.00168)
PDMP	-0.0338**	-0.0210	-0.0382**	-0.0407**	-0.0313**
	(0.0151)	(0.0151)	(0.0159)	(0.0177)	(0.0139)
PDMP * Policy Year	-0.0317***	-0.0514***	-0.0419***	-0.0370***	-0.0530***
	(0.00792)	(0.0140)	(0.0108)	(0.00912)	(0.0151)
Male	-	-	-0.0363***	-	-
	-	-	(0.00543)	-	-
Age (18-20)	0.0463***	0.0232	0.0426***	0.0501***	0.0227
	(0.0114)	(0.0160)	(0.0137)	(0.0128)	(0.0177)
Age (21-24)	0.0493***	0.0366*	0.0506**	0.0532***	0.0406*
	(0.0172)	(0.0201)	(0.0199)	(0.0191)	(0.0226)
Age (25-29)	0.0374***	0.0530***	0.0475***	0.0422***	0.0619***
	(0.0136)	(0.0201)	(0.0172)	(0.0157)	(0.0235)
Age (30-34)	0.0309***	0.0594***	0.0459***	0.0365***	0.0688***
	(0.0101)	(0.0168)	(0.0139)	(0.0121)	(0.0190)
Age (35-39)	0.0149**	0.0335***	0.0255***	0.0183***	0.0414***
	(0.00582)	(0.0102)	(0.00828)	(0.00691)	(0.0124)
HS Education	0.0102***	0.0148***	0.00998**	0.00901**	0.00974*
	(0.00362)	(0.00499)	(0.00454)	(0.00404)	(0.00578)
Veteran	-0.0112***	-0.0268***	-0.0184***	-0.0123***	-0.0290***
	(0.00201)	(0.00768)	(0.00210)	(0.00228)	(0.00889)
ln(Population)	0.0198***	0.0219***	0.0288***	0.0280***	0.0298***
	(0.00669)	(0.00693)	(0.00814)	(0.00830)	(0.00790)
Income Per Capita	2.52e-06***	1.18e-06	2.24e-06**	2.61e-06***	1.09e-06
	(8.22e-07)	(9.87e-07)	(9.80e-07)	(9.74e-07)	(1.05e-06)
Observations	303,806	117,731	356,386	253,684	102,702
Cluster MSA	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

V Conclusion

Abating the opioid epidemic is a paramount concern in the U.S. When investigating the effect of public policies it is crucial that the multitude of mitigating factors are analyzed. Dampening an epidemic which has evolved from a legal drug and at times an effective mechanism in controlling pain has proven difficult. The chemical composition of opioid analgesics make it cumbersome to enact policies which accurately deter its abuse, as not all use can be categorized as abuse. The intent of the modern-era of PDMPs, is to prevent and deter the abuse of controlled substances, in this paper we focus on its impact on treatment admissions. In evaluating the efficacy of such policies intended to combat the opioid epidemic, it is imperative to examine whether they are having the intended effects on segments of the population that are most affected. This has not always been a given. The crack-cocaine epidemic enforcement did not succeed in ameliorating the effects amongst the communities hardest hit by that epidemic [Jonsson, 2003].

We find that the states which implemented a PDMP experience a decrease in treatment admissions for opioid abuse, between 2000 and 2012, when compared to non-PDMP states. Upon further analysis we observe that the magnitude of the effect varies across race and gender, but it is relatively consistent within age groups. Interestingly, the effects are concentrated among White individuals, and particularly more pronounced among White women. Our results may suggest, as other studies have, that PDMPs, as a preventive measure may, lead to a decrease in the use and prescribing of opioids. The demographic distinction is important given that prior literature may be underestimating the effect of government policies and efforts to curb the epidemic. Additionally, understanding the role women play in the epidemic is eminent in forecasting its long reaching effects. As the face of substance abuse morphs there can be dire consequences on child health and safety, birth effects, and labor force participation to name a few.

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VI Appendix

Table 10: **Characteristics of PDMPs**

Operational	State	Legislation	Monitoring Agency	Schedule II	Schedule III	Schedule IV	Schedule V
1994	Massachusetts	1992	Department of Health	yes	yes	yes	yes
1995	West Virginia	1995	Pharmacy Board	yes	yes	yes	no
1996	Utah	1995	Professional Licensing Agency	yes	yes	yes	yes
1997	Nevada	1995	Pharmacy Board	yes	yes	yes	no
1998	Indiana	1997	Professional Licensing Agency	yes	yes	yes	yes
1999	Kentucky	1998	Department of Health	yes	yes	yes	yes
2003	Virginia	2002	Professional Licensing Agency	yes	yes	yes	no
2004	Maine	2003	Substance Abuse Agency	yes	yes	yes	no
2004	Wyoming	2004	Pharmacy Board	yes	yes	yes	no
2005	Mississippi	2005	Pharmacy Board	yes	yes	yes	yes
2005	New Mexico	2004	Pharmacy Board	yes	yes	yes	yes
2006	Alabama	2004	Department of Health	yes	yes	yes	yes
2006	Ohio	2005	Pharmacy Board	yes	yes	yes	yes
2006	Tennessee	2003	Pharmacy Board	yes	yes	yes	yes
2007	Colorado	2005	Pharmacy Board	yes	yes	yes	yes
2007	North Carolina	2005	Substance Abuse Agency	yes	yes	yes	yes
2007	North Dakota	2005	Pharmacy Board	yes	yes	yes	yes
2008	Arizona	2007	Pharmacy Board	yes	yes	yes	no
2008	Connecticut	2006	Consumer Protection Agency	yes	yes	yes	yes
2008	Louisiana	2006	Pharmacy Board	yes	yes	yes	yes
2008	South Carolina	2006	Department of Health	yes	yes	yes	no
2009	Iowa	2006	Pharmacy Board	yes	yes	yes	no
2009	Vermont	2006	Department of Health	yes	yes	yes	no
2010	Minnesota	2007	Pharmacy Board	yes	yes	yes	no
2011	Alaska	2008	Pharmacy Board	yes	yes	yes	no
2011	Florida	2009	Department of Health	yes	yes	yes	no
2011	Kansas	2008	Pharmacy Board	yes	yes	yes	no
2011	Nebraska	2011	Department of Health	yes	yes	yes	yes
2011	New Jersey	2008	Law Enforcement	yes	yes	yes	yes
2011	Oregon	2009	Department of Health	yes	yes	yes	no
2011	South Dakota	2010	Pharmacy Board	yes	yes	yes	yes
2011	Washington	2007	Department of Health	yes	yes	yes	yes

Table 11: **Substances Abused**

	FREQUENCY	PERCENT
ALCOHOL	6,248,001	40.26
COCAINE/CRACK	1,667,476	10.75
MARIJUANA/HASHISH	2,672,994	17.23
HEROIN	2,194,805	14.14
NON-PRESCRIPTION METHADONE	46,662	0.3
PRESCRIPTION OPIATES	1,012,130	6.52
PCP	33,510	0.22
OTHER HALLUCINOGENS	14,896	0.1
METHAMPHETAMINE	1,019,920	6.57
OTHER AMPHETAMINES	71,114	0.46
OTHER STIMULANTS	10,997	0.07
BENZODIAZEPINES	108,986	0.7
OTHER NON-BENZODIAZEPINE TRANQUILIZERS	4,050	0.03
BARBITURATES SEDATIVES	9,161	0.06
OTHER NON-BARBITURATE	25,950	0.17
INHALANTS	10,512	0.07
OVER-THE-COUNTER MEDICATIONS	10,209	0.07
OTHER	83,932	0.54
MISSING	62,303	0.4
NONE	210,126	1.35

Table 12: **Admissions for Abuse Relative to Year from PDMP Implementation**

Time from Policy	Number of States	Opioid Abuse	Opioid Abuse Per State	Total Substance Abuse	Total Substance Abuse Per State	White Male Opioid Abuse Per State	White Male Total Substance Abuse Per State	White Female Opioid Abuse Per State	White Female Total Substance Abuse Per State
-11	8	6,467	808	252,752	31,594	405	14,902	332	6,747
-10	9	7,823	869	241,062	26,785	432	12,832	369	5,960
-9	11	10,643	968	296,696	26,972	481	13,443	414	6,249
-8	15	13,632	909	403,988	26,933	449	12,470	383	5,740
-7	18	18,765	1,043	499,933	27,774	493	12,682	443	5,833
-6	21	25,296	1,205	586,145	27,912	592	12,560	496	6,054
-5	23	30,431	1,323	634,275	27,577	662	12,877	533	6,034
-4	25	38,617	1,545	684,112	27,364	764	12,955	635	6,377
-3	26	52,063	2,002	744,441	28,632	972	13,547	833	6,733
-2	26	62,318	2,397	742,320	28,551	1,158	13,360	999	6,799
-1	26	75,644	2,909	749,460	28,825	1,381	13,760	1,245	7,121
0	26	96,730	3,720	824,190	31,700	1,799	15,063	1,584	8,001
1	26	90,847	3,494	814,223	31,316	1,714	14,788	1,427	7,698
2	18	55,879	3,104	574,271	31,904	1,474	14,556	1,235	7,292
3	17	58,436	3,437	524,934	30,878	1,603	13,243	1,361	6,958
4	15	58,274	3,885	440,986	29,399	1,905	13,477	1,652	7,335
5	11	42,308	3,846	303,632	27,603	1,848	13,261	1,690	6,856
6	8	26,246	3,281	140,002	17,500	1,562	7,714	1,474	4,817
7	5	10,300	2,060	53,134	10,627	1,023	4,672	897	2,692
8	3	10,520	3,507	46,648	15,549	1,665	6,949	1,567	4,225
9	1	4,188	4,188	26,915	26,915	1,857	9,714	1,878	6,089

Time from policy, indicates the nubmer of years prior or after PDMP implementation in a given year.
Total Substance includes admissions for all substance excluding marijuana per prior explaination

Table 13: **Admission for Alcohol Abuse**

Treatment: PDMP States - Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) LPM 2000-2012	(2) Probit 2000-2012
Time Trend	-0.00584	-0.00697
	(0.00713)	(0.00751)
PDMP	0.0508***	0.0498***
	(0.0154)	(0.0158)
PDMP * Policy Year	0.0262	0.0331
	(0.0287)	(0.0312)
Male	0.0817***	0.0850***
	(0.0123)	(0.0129)
White	0.0978***	0.101***
	(0.0248)	(0.0245)
HS Education	0.0728***	0.0739***
	(0.00422)	(0.00403)
Veteran	0.0517***	0.0424***
	(0.00842)	(0.00860)
ln(Population)	-0.0839***	-0.0885***
	(0.0147)	(0.0161)
Income Per Capita	-1.92e-06	-1.99e-06
	(3.26e-06)	(3.38e-06)
Constant	1.723***	-
	(0.197)	-
	Admission for Heroin Abuse	
Time Trend	-0.0190***	-0.0127***
	(0.00445)	(0.00296)
PDMP	-0.0159	-0.0149
	(0.0186)	(0.0269)
PDMP * Policy Year	0.00987	0.0123
	(0.0159)	(0.0102)
Male	-0.0121***	-0.0102***
	(0.00416)	(0.00263)
White	-0.00425	0.00123
	(0.00746)	(0.00551)
HS Education	-0.0194***	-0.0113***
	(0.00639)	(0.00348)
Veteran	-0.0388***	-0.0277***
	(0.00866)	(0.00554)
ln(Population)	0.0282***	0.0379***
	(0.00912)	(0.00903)
Income Per Capita	1.71e-05***	1.05e-05***
	(2.27e-06)	(1.27e-06)
Constant	-0.900***	-
	(0.158)	-
Observations	7,132,006	7,132,006
Cluster MSA	Yes	Yes
Robust SE	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table 14: **Aggreatged State-Level Admission for Opioid Abuse**

Treatment: PDMP States - Pre-modern & Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) OLS 1993-2000	(2) OLS 2000-2012
Time Trend	0.00265	0.0104***
	(0.00531)	(0.00242)
PDMP	-0.0258	0.0337*
	(0.0181)	(0.0177)
PDMP * Policy Year	0.00574	-0.00781
	(0.00503)	(0.00547)
Age (18-20)	-2.23e-05	-1.75e-05*
	(1.60e-05)	(9.81e-06)
Age (21-24)	-1.35e-05	2.05e-05**
	(1.44e-05)	(8.71e-06)
Age (25-29)	-2.78e-05	1.25e-05*
	(1.86e-05)	(7.59e-06)
Age (30-34)	-2.58e-05*	1.62e-05**
	(1.41e-05)	(7.88e-06)
Age (35-39)	-3.06e-05**	-1.07e-06
	(1.21e-05)	(6.09e-06)
Male_2	2.04e-05*	-4.44e-06
	(1.06e-05)	(4.43e-06)
HS Education_2	1.02e-05	-6.08e-06**
	(8.10e-06)	(2.45e-06)
Income Per Capita	-2.69e-06	-3.83e-07
	(4.12e-06)	(1.28e-06)
ln(population)	-2.40e-08	1.53e-08
	(1.80e-08)	(1.05e-08)
Constant	0.123	-0.0724
	(0.0909)	(0.0693)
Observations	72	328
Fixed Effects	Yes	Yes
Robust SE	Yes	Yes
R-squared	0.773	0.839

*** p<0.01, ** p<0.05, * p<0.1

Table 15: **Admission for Opioid Abuse by Health & Community Referral:** Stratified by Race and Gender

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) All Sexes All Races	(2) Male All Races	(3) Women All Races	(4) All Sexes White	(5) Male White	(6) Female White
Time Trend	0.0113***	0.0110***	0.0124***	0.0134***	0.0129***	0.0143***
	(0.000765)	(0.000840)	(0.000749)	(0.000883)	(0.000908)	(0.000865)
PDMP	0.0191***	0.0166***	0.0229***	0.0232***	0.0210***	0.0267***
	(0.00351)	(0.00373)	(0.00386)	(0.00424)	(0.00447)	(0.00456)
PDMP * Policy Year	-0.0135*	-0.0143*	-0.0133**	-0.0168*	-0.0174*	-0.0172**
	(0.00805)	(0.00864)	(0.00630)	(0.00910)	(0.00946)	(0.00734)
Male	-0.0246***	-	-	-0.0311***	-	-
	(0.00234)	-	-	(0.00228)	-	-
White	0.0586***	0.0579***	0.0668***	-	-	-
	(0.00638)	(0.00675)	(0.00537)	-	-	-
Age (18-20)	0.0373***	0.0480***	0.0405***	0.0514***	0.0618***	0.0570***
	(0.00486)	(0.00606)	(0.00483)	(0.00541)	(0.00630)	(0.00571)
Age (21-24)	0.0578***	0.0738***	0.0675***	0.0779***	0.0923***	0.0907***
	(0.00462)	(0.00593)	(0.00498)	(0.00610)	(0.00705)	(0.00633)
Age (25-29)	0.0614***	0.0741***	0.0720***	0.0805***	0.0907***	0.0931***
	(0.00433)	(0.00525)	(0.00466)	(0.00542)	(0.00592)	(0.00550)
Age (30-34)	0.0451***	0.0535***	0.0535***	0.0583***	0.0649***	0.0675***
	(0.00322)	(0.00378)	(0.00339)	(0.00378)	(0.00402)	(0.00381)
Age (35-39)	0.0243***	0.0302***	0.0298***	0.0313***	0.0360***	0.0370***
	(0.00237)	(0.00254)	(0.00256)	(0.00261)	(0.00271)	(0.00286)
HS Education	0.0173***	0.0183***	0.0203***	0.0232***	0.0253***	0.0279***
	(0.00174)	(0.00160)	(0.00156)	(0.00237)	(0.00231)	(0.00213)
Veteran	-0.0128***	-0.0170***	-0.0171***	-0.0139***	-0.0185***	-0.0192***
	(0.00175)	(0.00188)	(0.00189)	(0.00234)	(0.00241)	(0.00230)
ln(Population)	0.0142***	0.0147***	0.0149***	0.0193***	0.0178***	0.0192***
	(0.00354)	(0.00333)	(0.00373)	(0.00405)	(0.00394)	(0.00420)
Income Per Capita	-2.03e-06***	-2.25e-06***	-2.17e-06***	-2.32e-06***	-2.43e-06***	-2.38e-06***
	(6.30e-07)	(7.00e-07)	(5.74e-07)	(6.97e-07)	(7.18e-07)	(6.04e-07)
Observations	2,085,942	1,680,927	1,610,415	1,834,957	1,559,876	1,505,189
Cluster MSA	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table 16: **Admission for Opioid Abuse by Criminal Referral:** Stratified by Race and Gender

Treatment: PDMP States in Modern Era
Control: AR, GA, MD, MO, NH

VARIABLES	(1) All Sexes All Races	(2) Male All Races	(3) Women All Races	(4) All Sexes White	(5) Male White	(6) Female White
Time Trend	0.00699***	0.00548***	0.0133***	0.0102***	0.00814***	0.0175***
	(0.000618)	(0.000514)	(0.00108)	(0.000891)	(0.000752)	(0.00142)
PDMP	0.00446	0.00290	0.0110*	0.00468	0.00321	0.0103
	(0.00350)	(0.00289)	(0.00627)	(0.00560)	(0.00482)	(0.00867)
PDMP * Policy Year	-0.00741**	-0.00565**	-0.0147**	-0.0102*	-0.00798*	-0.0179**
	(0.00357)	(0.00288)	(0.00662)	(0.00525)	(0.00433)	(0.00876)
Male	-0.0256***	-	-	-0.0339***	-	-
	(0.00239)	-	-	(0.00280)		
White	0.0298***	0.0246***	0.0506***	-	-	-
	(0.00270)	(0.00242)	(0.00388)			
Age (18-20)	0.0119***	0.0128***	0.00749**	0.0168***	0.0195***	0.00644
	(0.00198)	(0.00179)	(0.00377)	(0.00290)	(0.00257)	(0.00511)
Age (21-24)	0.0277***	0.0259***	0.0343***	0.0392***	0.0381***	0.0418***
	(0.00318)	(0.00289)	(0.00512)	(0.00453)	(0.00425)	(0.00614)
Age (25-29)	0.0331***	0.0288***	0.0483***	0.0476***	0.0431***	0.0605***
	(0.00329)	(0.00296)	(0.00538)	(0.00465)	(0.00443)	(0.00610)
Age (30-34)	0.0268***	0.0213***	0.0445***	0.0390***	0.0323***	0.0560***
	(0.00264)	(0.00237)	(0.00458)	(0.00383)	(0.00367)	(0.00488)
Age (35-39)	0.0159***	0.0124***	0.0263***	0.0236***	0.0192***	0.0331***
	(0.00170)	(0.00162)	(0.00281)	(0.00258)	(0.00246)	(0.00393)
HS Education	0.00142	9.30e-05	0.00544***	0.00129	-0.000120	0.00481**
	(0.00114)	(0.000974)	(0.00184)	(0.00171)	(0.00154)	(0.00237)
Veteran	-0.00456***	-0.00392***	-0.00277	-0.00650**	-0.00553***	-0.00398
	(0.00172)	(0.00129)	(0.00469)	(0.00253)	(0.00196)	(0.00605)
ln(Population)	0.0136***	0.0107***	0.0244***	0.0222***	0.0179***	0.0360***
	(0.00221)	(0.00174)	(0.00416)	(0.00328)	(0.00260)	(0.00567)
Income Per Capita	-9.47e-07**	-5.42e-07	-2.78e-06***	-1.62e-06**	-9.68e-07*	-4.18e-06***
	(4.09e-07)	(3.40e-07)	(6.92e-07)	(6.42e-07)	(5.42e-07)	(9.84e-07)
Observations	2,704,122	2,040,113	664,009	1,888,885	1,393,334	495,551
Cluster MSA	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1