The Association Between State Prescription Drug Monitoring Programs and Fatal Opioid Overdoses

Henry Siegler
California Polytechnic State University, San Luis Obispo

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Abstract

Opioid overdose rates have been steadily on the rise in the United States since the late 1990s. In response, Prescription Drug Monitoring Programs have been implemented in 49 states and the District of Columbia to collect and distribute information on controlled substances. The objective of this analysis is to examine the association between establishing an operational PDMP and opioid overdose rates, while also examining how these associations vary for different categories of opioids. Opioid overdose death rates were gathered for each state from 2000 to 2020 from the CDC Wonder database, along with data on the year when a state implemented an operational PDMP. The findings indicate that states with operational PDMPs experience an average reduction of 0.795 opioid overdose deaths per 100,000 people annually, in comparison to states without a PDMP. The results are similar in magnitude to previous studies regarding the effectiveness of PDMPs in reducing opioid overdoses.

JEL: I18, H75, C33

Key Words: Prescription Drug Monitoring Programs, Opioid Overdose Rates, Prescriptions, CDC WONDER database, Healthcare Providers, Regulation

1. Introduction

The United States is currently in the midst of an opioid epidemic, which has emerged as a significant concern over the past few decades. The number of deaths caused by opioid overdoses has been rapidly increasing since 2000 (CDC WONDER, 2023). According to the U.S. Department of Health and Human Services (2023), opioid overdose deaths rose from 21,089 in 2010 to 47,600 in 2017.

Both the U.S. federal government and state governments have implemented several measures to fight the opioid overdose epidemic. These actions include identifying outbreaks, collecting data, and providing care to affected communities. Among the strategies employed today, Prescription Drug Monitoring Programs (PDMPs) stand out as a particularly promising state-level intervention. PDMPs are electronic databases that track controlled substance prescriptions within a state, accessible by health authorities and healthcare providers (Centers for Disease Control and Prevention, 2022c). PDMPs aim to enhance opioid prescribing practices and reduce the diversion of these substances. It is crucial to understand the impact and effectiveness of these programs in combatting the opioid epidemic so that resources can be allocated most effectively. In this analysis, observational data is used to estimate the association between the implementation of an operational PDMP and opioid overdose rates for different categories of opioids.

Some researchers have suggested that PDMPs can be effective at reducing opioid overdoses (Patrick et al., 2016). According to this theory, healthcare providers reference PDMPs to regulate the number of opioids they prescribe, specifically to individuals who already received an adequate amount for their condition. This objective is believed to reduce the number of people dependent on opioids, consequently lowering both prescription opioid overdoses and opioid overdoses from illicit markets. However, findings in this area are mixed, and alternative perspectives argue that PDMPs are not associated with decreases in opioid-related overdoses (Nam et al., 2017). Critics propose that PDMPs have a minimal effect on the consumption of opioids and emphasize the need for PDMP managers to enhance the utilization of their data to address the issue of rising opioid overdose rates (Paulozzi et al., 2011).

Between 2000 and 2020, a total of 33 states implemented operational PDMPs. However, limited research has examined whether PDMPs have the same impact on opioid overdoses across different categories of opioids. Additionally, much of the previous literature has focused on a relatively short time frame, potentially resulting in estimates that may differ significantly when considering more recent data. The objective of this analysis is to examine the association between a state's operational PDMP status and opioid overdose rates. It is expected that the implementation of operational PDMPs in a state is associated with a decrease in the opioid overdose death rate across all categories of opioids.

2. Literature Review

Previous research has yielded inconsistent findings regarding the impact of PDMPs on reducing opioid overdose death rates. Numerous studies have explored the relationship between PDMP implementation and various negative opioid-related outcomes.

Cerda et al. (2021) investigate the association between state-level PDMPs and county-level fatal prescription opioid overdoses. The authors analyze county-level data from 3,109 counties in 49 states, covering the period from 2002 to 2016, to estimate the impact of electronic PDMP access on opioid overdoses. The results of the study indicate that electronic PDMPs are associated with a 9% decrease in rates of fatal prescription opioid overdoses after three years, with well-supported effects for methadone and synthetic opioids.

In a similar study, Patrick et al. (2016) employ an interrupted time-series design to estimate the association between the implementation of PDMPs, as well as specific program characteristics, and opioid overdose rates. The annual rate of opioid-related overdose deaths in each state was obtained from the CDC Wonder database, spanning the years 1999 to 2013. The study findings indicate that states newly implementing a PDMP were associated with a decrease of 1.12 opioid-related overdose deaths per 100,000 individuals annually compared to states without a program. Furthermore, the researchers conclude that PDMPs monitoring four or more drug schedules and updating their data at least weekly were predicted to have 1.55 fewer opioid-related overdose deaths per 100,000 population annually compared to states without a program. However, this study did not evaluate how PDMP implementation affects death rates for different types of opioids, such as prescription opioids or illicitly manufactured opioids. Nevertheless, the study results strongly suggest that implementing PDMPs is associated with significant reductions in opioid-related death rates, thereby contributing to the body of evidence highlighting the effectiveness of PDMPs.

Further evidence on the effectiveness of PDMPs has been conducted by Reifler et al. (2012), who aim to assess whether PDMPs have an impact on state-level trends in opioid abuse. The researchers use quarterly data from 2003 to 2009 from the RADARS System Poison Center and Opioid Treatment surveillance databases to measure the level of opioid abuse in each state. Their findings indicate that states without a PDMP experienced an average quarterly increase of 4.9% in opioid treatment admissions, while states with a PDMP witnessed a lower increase of 2.6%. These results suggest that PDMPs are successful programs at reducing overall opioid misuse and abuse, with the analysis utilizing a different dependent variable other than overdose rates. One limitation of this study is that the treatment admission data is subject to self-reporting and selection bias, which may lead to inaccurate numbers.

However, there are studies that present contrasting findings and do not support the notion that PDMPs effectively reduce negative outcomes associated with opioids. In a study conducted by Nam et al. (2017), the researchers collect mortality rate data from the CDC Wonder database, as well as other individual-level unsuppressed mortality data, covering the period from 1999 to 2010. They find that PDMPs were not associated with a decrease in the overdose mortality rate for overall opioids, prescription opioids, and legal narcotics. Furthermore, the researchers observe that PDMPs are often linked to increased mortality rates for illicit drugs, suggesting that restricted access to prescription drugs may lead individuals with addictive disorders to seek out substitute drugs. This study suggests that PDMPs may not fully address the issues of prescription diversion, doctor shopping, and other similar behaviors. Additionally, it raises the possibility that PDMPs may discourage patients from seeking help from doctors who could assist them in addressing drug abuse.

In another study conducted by Paulozzi et al. (2011), the researchers analyze state-level data on opioid overdose mortality rates and opioid drug consumption using observational data in the United States from 1999 to 2005. Mortality data is obtained from the CDC Wonder database, while retail distributions of prescription opioids are obtained from the ARCOS database of the United States DEA. The study findings indicate that the presence of a PDMP is not a significant predictor of mortality or prescription opioid distribution rates. The authors acknowledge the primary limitation of the study, which is the inability to rule out residual confounding. It is possible that states with a predisposition towards drug abuse initially had higher drug overdose rates, making them more likely to establish a PDMP. Additionally, the study is limited by its relatively short time frame, spanning only from 1999 to 2005.

The existing body of literature on the effectiveness of PDMPs in mitigating negative outcomes related to opioids presents mixed findings. Overall, previous studies have indicated that the impact of PDMPs on opioid-related outcomes is not highly substantial, even in cases where PDMPs have shown some effectiveness. It is worth noting that, except for a specific subset of the study by Nam et al. (2017), there is no evidence suggesting that the implementation of PDMPs is associated with increases in opioid deaths or dispensing. While the evidence regarding the efficacy of PDMPs remains inconclusive, it does not appear that there are significant unintended consequences associated with the implementation of these programs.

Economic Theory

The goal of this empirical analysis is to examine the association between opioid overdose rates and operational PDMPs. The choice to utilize the year of PDMP operational status, as opposed to the year of legislative authorization, is because the operational date signifies when the program is actively functioning, and healthcare providers are accessing the information (PDAPS, 2017). The operational date provides a more accurate representation of when the PDMP is actively in use by healthcare providers.

PDMPs serve as a valuable tool for opioid prescribers by providing them with enhanced patient information, thus improving their ability to identify individuals who may be at a higher risk of opioid abuse or overdose. These programs may also impose limitations on the prescription of certain drugs or require prescribers to adhere to stricter guidelines (Centers for Disease Control and Prevention, 2022c). The underlying goal of PDMPs is to effectively regulate the distribution of opioids and curb diversion, ultimately reducing the availability of opioids to individuals who are most vulnerable to misuse. It is expected that levels of opioid use will decrease after PDMP implementation, subsequently leading to a decline in opioid overdose incidents. The diminished accessibility to opioids should also contribute to a decrease in addiction rates over time, ultimately resulting in a further reduction in opioid overdose fatalities.

It is important to note that the impact of PDMPs on the opioid overdose rate may not be immediate upon implementation. While PDMPs may not have a significant effect on reducing the overdose rates among individuals already engaged in opioid use prior to their implementation, they have the potential to limit future exposure to opioids and prevent the development of additions among individuals who currently use these drugs. The underlying assumptions of this model are that healthcare providers consider information from the PDMPs before prescribing opioids and that a substantial portion of the opioids used by the population originate from prescription sources.

In this analysis, the opioid death rates are categorized into four distinct categories.

The first category encompasses all opioids and serves as a measure of the entire opioid overdose issue in each state and year. It includes both prescription opioids and illicitly manufactured opioids, providing a comprehensive view of the total opioid overdose rate.

The second category focuses specifically on heroin and synthetic opioid analgesics other than methadone. This category measures the overdose rates related to illicitly manufactured opioids, which are not regulated by PDMPs since they are not prescribed. Heroin is a Schedule 1 substance under the Controlled Substances Act, meaning that there is no currently accepted medical use of heroin in the United States (Drug Enforcement Administration, 2020). Synthetic opioid overdoses are largely driven by illicitly manufactured fentanyl-involved overdoses (Centers for Disease Control and Prevention, 2022b).

The third category includes natural opioid analgesics, semisynthetic opioids, in addition to other and unspecified narcotics. This category will be referred to as the prescription opioid overdose rate and it encompasses commonly prescribed opioids such as morphine, codeine, oxycodone, hydrocodone, hydromorphone, and oxymorphone (National Center for Health Statistics, 2023). According to the Centers for Disease Control and Prevention (2022d), these opioids are among the most frequently prescribed opioids.

The fourth and final category focuses on methadone only. Methadone, used for severe pain management and opioid addiction treatment, is one of the most prescribed opioids (CAMH, 2021). This category helps assess the overdose levels specific to methadone, providing additional insights into the impact of PDMPs on prescription opioid overdose rates.

It is expected that the overdose death rates for all categories of opioids in a state would decrease after the implementation of an operational PDMP. The effectiveness of PDMPs is expected to be more pronounced in the case of prescription opioids compared to illicitly manufactured opioids. This arises from the fact that PDMPs regulate prescription opioids specifically. However, it is still expected that PDMPs would be associated with lower overdose rates related to illicitly manufactured opioids. This is because many illicit opioid users initially started with the use of prescription opioids (Utah Department of Health, 2018).

3. Data and Methodology

Data

This analysis uses observational state-year-level data from 2000 to 2020. In this analysis, the four dependent variables used in the various models are the total opioid overdose rate, the heroin and synthetic opioid overdose rate, the prescription opioid overdose rate, and the methadone overdose rate. These data were obtained from the CDC Wonder Multiple Cause of Death database, which included the death counts and populations in each state-year pair for various categories of opioid overdoses. In this analysis, the multiple causes of death ICD-10 codes were used to categorize the type of opioid overdose. Codes T40.1-T40.4 and T40.6 were used to calculate the total opioid overdose rate, codes T40.1 and T40.4 for the heroin and synthetic opioid overdose rate, codes T40.2 and T40.6 for the prescription opioid overdose rate, and code T40.3 for the methadone overdose rate (CDC WONDER, 2023).

For each of the four overdose rates, there were missing values, generally for the less populous states in the earlier years of the study. The CDC Wonder database suppresses mortality data when the number of deaths is fewer than 10. The methadone overdose rates for North Dakota, South Dakota, and Wyoming were missing for all years, so those three states were removed from the regression that uses the methadone overdose rate as the dependent variable. After completely removing the three states for the methadone rate, 5.4% of the overdose rates were missing.

Linear imputation was applied to fill in the missing values individually for each state and overdose rate. Data from the years before and after the missing observations were used to linearly impute the missing values for each state and overdose rate individually.

Using data from the Prescription Drug Abuse Policy System, an indicator variable was created to indicate whether an operational PDMP was in place in a given state and year (PDAPS, 2017).

Data were also obtained for various covariates in the models. Median income data were obtained for each state-year pair and were converted to thousands of dollars in the model (US Census Bureau, 2022). Using the IPUMS USA Community Survey, data were obtained on the percentage of the state that identified as white, the unemployment rate, the percentage of the state with a bachelor's degree or higher, and the average age for each state-year pair (IPUMS USA, 2022). These percentages and estimates were calculated after accounting for the person weight variable in the data, which indicates how many individuals in the US population are represented by a given individual in the survey sample. Finally, personal health care spending per capita in thousands of dollars was obtained as an additional covariate in the models (Centers for Medicare & Medicaid Services, 2023).

Stylized Facts

Fig. 1 shows the total number of operational PDMPs in effect in each year of this study. In 2000, the first year in this analysis, there were 16 operational PDMPS in place. By 2014, there were 50 operational PDMPS in effect, leaving Missouri as the only state without an operational PDMP. From 2002 to 2014, 34 states implemented an operational PDMP, and new PDMPs were implemented in each of those years.

Fig. 2 plots the average total opioid overdose rate among states with and without an operational PDMP in effect by year. Fig. 2 demonstrates that the average opioid overdose rates for states with and without an operational PDMP in effect have been very similar and have increased in a parallel fashion since 2000. From 2000 to 2010, the average overdose rate among states with an operational PDMP was higher by about 1.5 overdoses compared to the average among states without an operational PDMP in effect. After 2010, the average overdose rates were very similar. It is important to note that the number of states with no operational PDMP in effect is decreasing over this time frame, so differences in the average overdose rates are likely due to fluctuations in the rates of only a few states. By 2014, Missouri was the only state that did not have a PDMP, so the average overdose rate for the group with no operational PDMP after 2013 is simply the overdose rate in Missouri.

Fig. 3 plots the median overdose rate among the states in each year for the four categories of opioids in this analysis. The median total opioid overdose rate increased steadily from 2000 to 2012 and then rose greatly thereafter due to significant increases in overdose deaths involving synthetic opioids, primarily illicitly manufactured fentanyl. The median overdose rates for methadone and the natural and semisynthetic opioid categories increased greatly during the 2000s but did not significantly increase since. The median methadone overdose rate has even decreased since 2010. During the 2010s the increase in the total opioid overdose rates can be attributed to the rise in heroin and synthetic opioid overdose deaths, largely due to illicitly manufactured fentanyl (Centers for Disease Control, 2022).

Fig. 4 provides a comprehensive overview of the distribution of the total opioid overdose rates across the 50 states and the District of Columbia. The table displays quantiles of opioid overdose rates among the states, representing the values at which a particular percentage of states fall below for select years. Fig. 4 demonstrates that there has been a consistent rise in overdose rates for states across the country, indicating that increases in average and median overdose rates are not only being driven by increases in some states. This indicates a widespread and escalating problem affecting all regions across the country.

Empirical Regression

This analysis uses a panel data model with state-year fixed effects to examine the association between having an operational PDMP in a given state and year and various opioid overdose death rates. This model treats states without an operational PDMP as control states and the differential timing of states creating operational PDMPs is used to estimate the association between operational PDMPs and opioid overdoses. The panel data regression equations are of the following form:

$$Y_{s,t} = \alpha_s + \gamma_t + \beta_1 PDMP_{s,t} + \sum_{k=1}^{K} \theta_k X^k_{s,t} + \epsilon_{s,t}$$

Where $Y_{s,\,t}$ is the overdose death rate for state *s* in time *t*, α_s are state-fixed effects, and γ_t are year-fixed effects. *PDMP* is a binary variable equal to 1 for state-year pairs with an operational PDMP and 0 otherwise. The vector of the covariates contains the following characteristics of a state-year pair: the average age, the percentage of the state with a bachelor's degree or higher, the median income in thousands of dollars, the unemployment rate, the percentage of the state that identifies as white, and the personal health care spending per capita in thousands of dollars. The four overdose rates that will be used as dependent variables are the total opioid overdose rate, the heroin and synthetic opioid overdose rate, the prescription overdose rate, and the methadone overdose rate.

To assess the robustness of the findings, an alternative model was estimated for each of the overdose rates that did not include the covariates, and only included the state and year-fixed effects. These models are of the following form:

$$Y_{s,\,t} = \alpha_s + \gamma_t + \beta_1 PDMP_{s,\,t} + \epsilon_{s,\,t}$$

These alternative estimates aim to test the robustness and validity of the results by assessing if they hold when not including potential confounding variables. Comparing the two models for each overdose rate will help to assess whether the relationships are driven by the variables of interest themselves or if they are influenced by the inclusion of other factors.

The coefficient of interest in these models is the coefficient for the *PDMP* variable. β_1 can be interpreted as the average change in the overdose rate associated with the establishment of a PDMP, after controlling for state and year-fixed effects, and the covariates in the model. Consistent with economic theory, it is expected that operational PDMPs are associated with lower overdose rates for all types of opioids. PDMPs are hypothesized to reduce levels of opioid misuse, mitigate opioid diversion, and deter individuals from resorting to illicitly manufactured opioids. Therefore, it is expected that the coefficient of *PDMP* will be negative, indicating a lower overdose death rate on average for states with an operational PDMP compared to those without one.

By including a fixed effects model with both year and state-fixed effects, the models control for unobserved time-varying and state-specific confounders that could influence the opioid overdose death rate. Robust standard errors are reported in each panel data model.

4. Results

Table 1 displays the results from estimating the panel data regression equations with the total opioid overdose rate per 100,000 people as the dependent variable. The estimates in Column (1) of Table 1 display the results without any covariates. The *PDMP* coefficient estimate is -0.526 but is statistically insignificant in the model without covariates. However, Column (2) of Table 1 shows the results with additional control variables. The *PDMP* coefficient in the model is -0.795 and is significant at the 10% level. The change in the magnitude of the coefficient on the *PDMP* variable indicates that the relationship between PDMPs and the opioid overdose rate is driven by other factors. This estimate suggests that states with an operational PDMP are estimated to have 0.795 fewer opioid overdose deaths per 100,000 people on average, compared to states without a PDMP. The average total opioid overdose rate per 100,000 people over all states in this analysis was 9.5 overdoses per 100,000 people, so this estimated reduction is significant.

Table 2 displays the results for the models using the heroin and synthetic opioid overdose rate per 100,000 as the dependent variable. Column (1) of Table 2 is based on the regression without covariates, and the estimate of the *PDMP* coefficient is statistically insignificant. In Column (2) of Table 2, the estimate in the model with all the covariates included is -0.728 and is significant at the 10% level. This estimate suggests that states with an operational PDMP are estimated to have 0.728 fewer heroin and synthetic opioid overdose deaths per 100,000 people on average, compared to states without a PDMP. For reference, the average heroin and synthetic opioid overdose rate across all years and states in this analysis is 5.06 overdoses per 100,000, so this estimated decrease in the overdose rate of 0.728 overdoses is very significant.

The results from estimating the PDMP effect on the prescription opioid overdose rate are displayed in Table 3. Column (1) of Table 3 shows the *PDMP* coefficient estimate without covariates, which is -0.345 and is significant at the 5% level. After adding the covariates, the estimate changes to -0.329, which is significant at the 10% level. This estimate suggests that states with an operational PDMP are estimated to have 0.329 fewer prescription opioid overdose deaths per 100,000 people on average. Given that the average overdose death rate of this opioid category over all the states and years is 4.51 overdoses per 100,000, this decrease is still sizeable.

The estimates of the operational PDMP effect on the methadone overdose rate per 100,000 are displayed in Table 4. The *PDMP* estimate in Column (1) in Table 4 of 0.017 is not statistically significant. The estimate in Column (2) of Table 4 with the covariates moves to -0.009, but this estimate is also not statistically significant. Table 4 provides evidence that operational PDMPs are not associated with any changes in methadone overdose rates. Table 5 displays the same estimates in Tables 1-4 for the models with the covariates.

These results suggest that PDMPs are associated with similar reductions in heroin and synthetic overdoses compared to prescription opioid overdoses, which was not expected because PDMPs do not regulate the distribution of heroin and fentanyl, which constitute most overdoses in that category. Heroin and synthetic opioid overdose rates have been higher on average compared to prescription opioid overdose rates, so the larger magnitude of the PDMP coefficient estimate for heroin and synthetic opioids is really similar to the estimate in the prescription opioid model in terms of their relative effects. PDMPs were associated with significant reductions in prescription opioid overdoses, however, they were not associated with reductions in the methadone overdose rate, which serves as a secondary category of prescription opioids.

The results of this study are similar to those in the study by Patrick et al. (2016) which indicated that PDMPs were associated with a decrease of 1.12 opioid-related overdose deaths per 100,000 annually compared to states without a program. The estimated reduction of 0.795 deaths per 100,000 annually in this study provides evidence that when also considering more recent data after 2013, the estimated reduction does not appear to be as high. Cerda et al. (2021) found PDMPs to be associated with reductions in overdose rates for prescription opioids and synthetic opioids, which was also the conclusion of this study. However, Cerda et al. (2021) found that PDMPs were associated with reductions in the overdose rate for methadone, but in this study, there was no evidence of that association.

It is important to note that there are various limitations to this study. First, observational data was used, so causality cannot be established. In addition, each source of data had its own potential sources of error. For example, opioid-related overdose deaths may be underreported if toxicology testing is not conducted. Also, it is possible that not every important state-level confounder was accounted for. Finally, it is likely that states did not implement their PDMPs at random times. For example, it is possible that in response to higher opioid overdose rates or opioid-related issues, states could have been more influenced to implement a PDMP.

5. Conclusion

This study attempts to provide an estimate of the association between implementing an operational PDMP and overdose death rates for various categories of opioids. PDMPs provide healthcare providers with reliable information on the prescriptions of their patients, which likely leads to lower levels of opioid diversion and opioid misuse.

The results of this study suggest that states with operational PDMPs are expected to experience reductions of about 0.795 opioid-related overdoses per 100,000 people annually, compared to states with a PDMP. This means that for a state like California, with a population of about 39 million, we would have expected there to have been about 310 more opioid overdoses annually on average if California had never established a PDMP.

The results indicate that relative to the average overdose rates for the various categories of opioids, the reductions in overdose rates associated with PDMPs for prescription opioids and illicitly manufactured opioids are very similar. PDMPs were not associated with reductions in methadone overdose rates, which suggests that PDMPs may not be associated with reductions in overdose rates for all types of prescription opioids.

Future studies should focus on analyzing what characteristics of PDMPs have shown to be the most effective at reducing negative opioid-related outcomes, such as how frequently data is updated and how data is shared between states. Also, future studies should focus on controlling for other state-level programs and actions that have been taken over time that may have had an impact on opioid overdoses in that state.

Creating well-funded and well-functioning PDMPs is unlikely to solve the opioid epidemic, but the evidence of a significant reduction in the opioid overdose death rate after PDMP implementation is economically significant and demonstrates that PDMPs are an effective action to combat this problem. Policymakers should consider improving funding for PDMPs and improving interstate operability. These results also suggest that other related efforts to combat the epidemic may also be worthwhile.

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Figure 1:

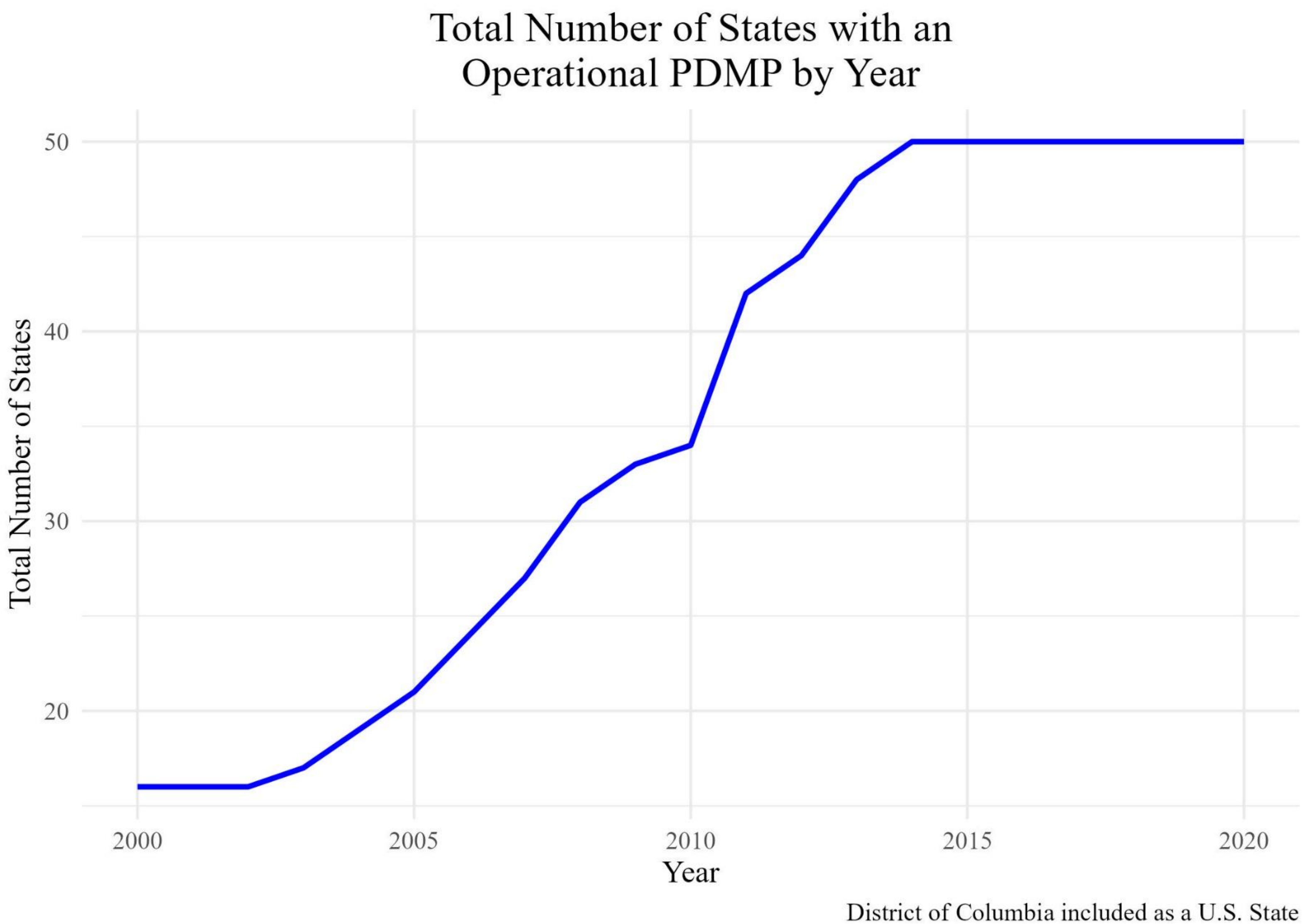
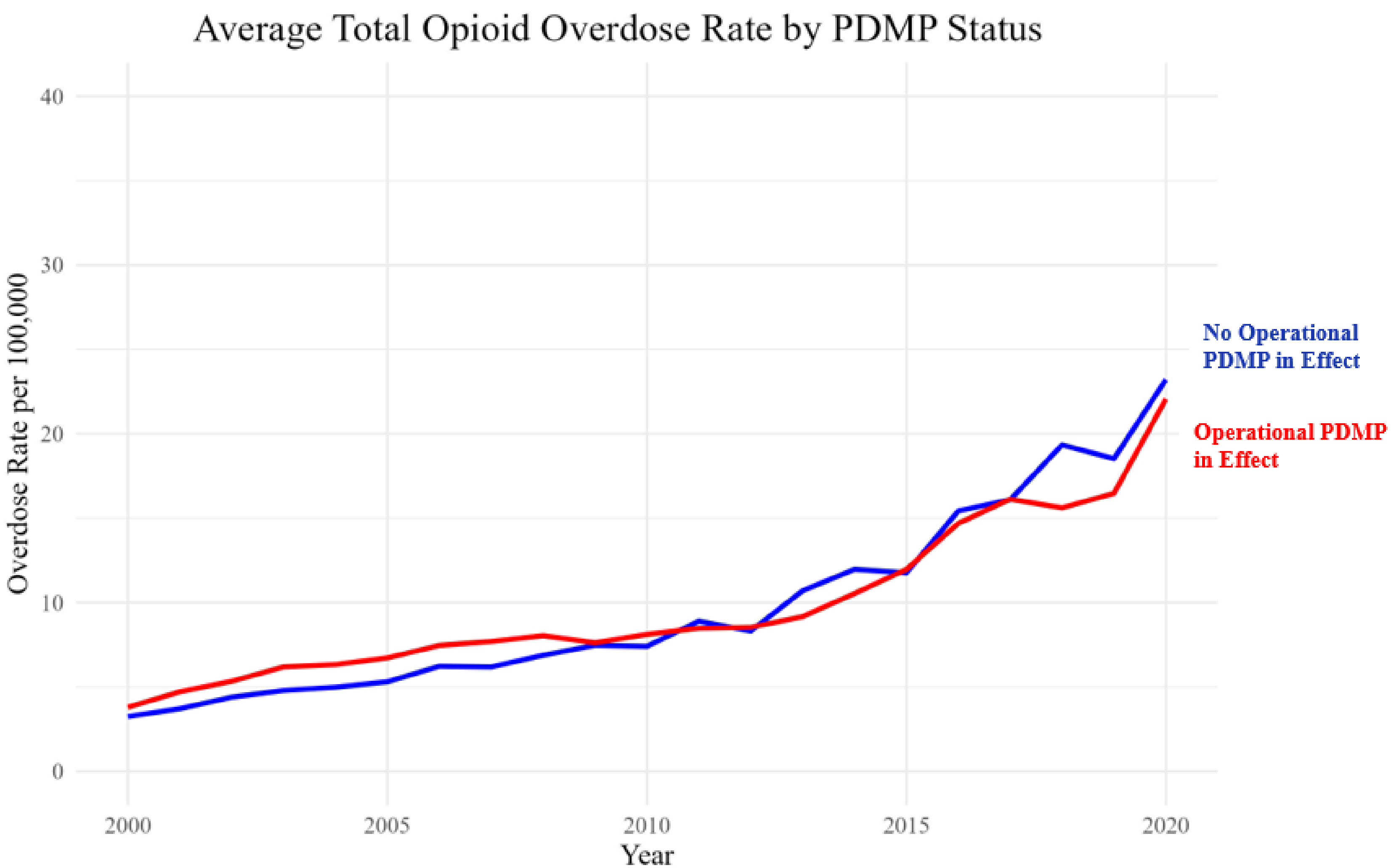
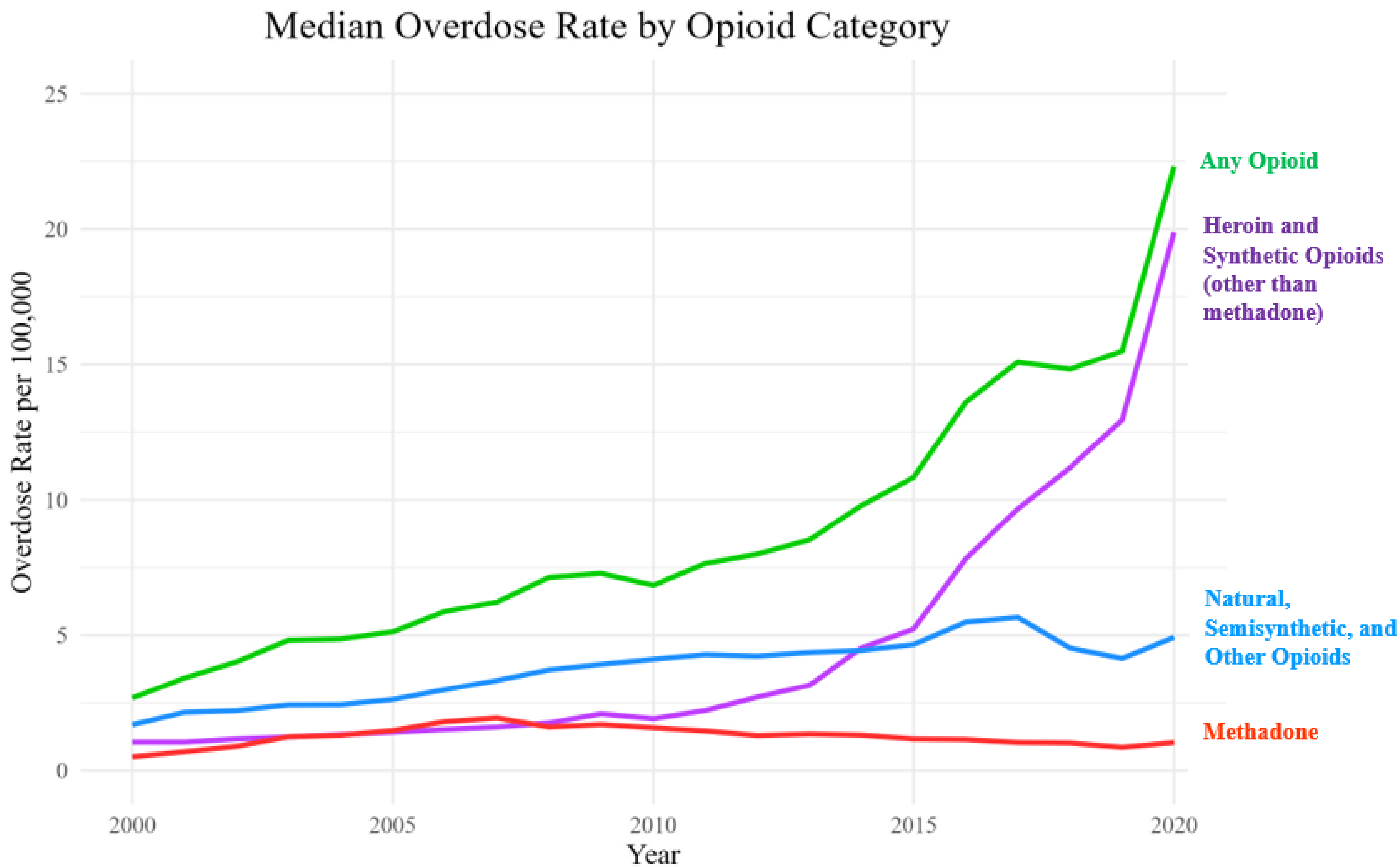

Total Number of States with an Operational PDMP by Year
50
40
30
20
Total Number of States
2000
2005
2010
2015
2020
Year
District of Columbia included as a U.S. State

Figure 2:



Average Total Opioid Overdose Rate by PDMP Status
Overdose Rate per 100,000
40
30
20
10
0
2000
2005
2010
2015
2020
Year
No Operational PDMP in Effect
Operational PDMP in Effect

Figure 3:



Median Overdose Rate by Opioid Category
25
20
15
10
5
0
Overdose Rate per 100,000
2000
2005
2010
2015
2020
Year
Any Opioid
Heroin and Synthetic Opioids (other than methadone)
Natural, Semisynthetic, and Other Opioids
Methadone

Figure 4:

Quantiles of Overdose Rates across 50 U.S. States and the District of Columbia in Select Years

Year	5%	25%	50%	75%	95%
2000	0.76	1.89	2.69	4.45	8.45
2005	2.05	3.62	5.13	7.86	11.38
2010	3.44	5.1	6.85	9.7	14.16
2020	6.48	12.25	22.31	29.04	41.97

Note: Overdose rate is measured as the number of overdoses per 100,000 people.

Table 1:

	Dependent Variable: Total Opioid Overdose Death Rate per 100,000	
	(1)	(2)
PDMP in Operation	−0.526	−0.795*
	(0.471)	(0.443)
Average Age		1.372***
		(0.424)
Percentage with Bachelor's Degree		1.196***
		(0.275)
Median Income		−0.049
		(0.045)
Unemployment Rate		−0.090
		(0.160)
Percentage that is White		0.190**
		(0.097)
Personal Healthcare Spending per Capita		2.997***
		(0.503)
Constant	−1.289*	−86.595***
	(0.683)	(16.531)
Fixed Effects	Yes	Yes
Covariates	No	Yes
Observations	1,071	1,071
R^2	0.721	0.764
Adjusted R^2	0.701	0.746
Residual Std. Error	4.240 (df = 999)	3.912 (df = 993)
F Statistic	36.363*** (df = 71; 999)	41.724*** (df = 77; 993)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2:

	Dependent Variable: Heroin and Synthetic Opioid Overdose Death Rate per 100,000	
	(1)	(2)
PDMP in Operation	−0.430	−0.728*
	(0.454)	(0.415)
Average Age		1.860***
		(0.399)
Percentage with Bachelor's Degree		1.624***
		(0.257)
Median Income		−0.021
		(0.045)
Unemployment Rate		0.005
		(0.143)
Percentage that is White		0.184*
		(0.096)
Personal Healthcare Spending per Capita		2.940***
		(0.542)
Constant	−1.400**	−111.298***
	(0.701)	(16.149)
Fixed Effects	Yes	Yes
Covariates	No	Yes
Observations	1,071	1,071
R^2	0.681	0.748
Adjusted R^2	0.658	0.729
Residual Std. Error	4.167 (df = 999)	3.710 (df = 993)
F Statistic	29.990*** (df = 71; 999)	38.359*** (df = 77; 993)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3:

	Dependent Variable: Prescription Opioid Overdose Death Rate per 100,000	
	(1)	(2)
PDMP in Operation	-0.345^{**}	-0.329^{*}
	(0.168)	(0.170)
Average Age		-0.017
		(0.140)
Percentage with Bachelor's Degree		-0.273^{***}
		(0.085)
Median Income		-0.036^{**}
		(0.017)
Unemployment Rate		-0.146^{**}
		(0.068)
Percentage that is White		-0.001
		(0.030)
Personal Healthcare Spending per Capita		0.241
		(0.153)
Constant	-0.187	5.971
	(0.287)	(5.515)
Fixed Effects	Yes	Yes
Covariates	No	Yes
Observations	1,071	1,071
R^2	0.740	0.747
Adjusted R^2	0.721	0.727
Residual Std. Error	1.583 (df = 999)	1.567 (df = 993)
F Statistic	40.004^{***} (df = 71; 999)	38.039^{***} (df = 77; 993)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4:

	Dependent Variable: Methadone Overdose Death Rate per 100,000	
	(1)	(2)
PDMP in Operation	0.017	−0.009
	(0.070)	(0.068)
Average Age		0.074
		(0.073)
Percentage with Bachelor's Degree		0.092**
		(0.037)
Median Income		0.009
		(0.007)
Unemployment Rate		0.071**
		(0.028)
Percentage that is White		0.007
		(0.014)
Personal Healthcare Spending per Capita		0.163***
		(0.061)
Constant	0.282***	−5.506*
	(0.093)	(3.019)
Fixed Effects	Yes	Yes
Covariates	No	Yes
Observations	1,008	1,008
R^2	0.664	0.679
Adjusted R^2	0.640	0.653
Residual Std. Error	0.607 (df = 939)	0.596 (df = 933)
F Statistic	27.295*** (df = 68; 939)	26.625*** (df = 74; 933)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5:

	Dependent Variable: Overdose Death Rate per 100,000 for Four Categories of Opioids:			
	All	Heroin and Synthetic	Prescription	Methadone
	(1)	(2)	(3)	(4)
PDMP in Operation	−0.795*	−0.728*	−0.329*	−0.009
	(0.443)	(0.415)	(0.170)	(0.068)
Average Age	1.372***	1.860***	−0.017	0.074
	(0.424)	(0.399)	(0.140)	(0.073)
Percentage with Bachelor's Degree	1.196***	1.624***	−0.273***	0.092**
	(0.275)	(0.257)	(0.085)	(0.037)
Median Income	−0.049	−0.021	−0.036**	0.009
	(0.045)	(0.045)	(0.017)	(0.007)
Unemployment Rate	−0.090	0.005	−0.146**	0.071**
	(0.160)	(0.143)	(0.068)	(0.028)
Percentage that is White	0.190**	0.184*	−0.001	0.007
	(0.097)	(0.096)	(0.030)	(0.014)
Personal Healthcare Spending per Capita	2.997***	2.940***	0.241	0.163***
	(0.503)	(0.542)	(0.153)	(0.061)
Constant	−86.595***	−111.298***	5.971	−5.506*
	(16.531)	(16.149)	(5.515)	(3.019)
Fixed Effects	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Observations	1,071	1,071	1,071	1,008
R^2	0.764	0.748	0.747	0.679
Adjusted R^2	0.746	0.729	0.727	0.653
Residual Std. Error	3.912 (df = 993)	3.710 (df = 993)	1.567 (df = 993)	0.596 (df = 933)
F Statistic	41.724*** (df = 77; 993)	38.359*** (df = 77; 993)	38.039*** (df = 77; 993)	26.625*** (df = 74; 933)

Note: *p<0.1; **p<0.05; ***p<0.01