County Level Assessment of Prescription Drug Monitoring Program and Opioid Prescription Rate

Abstract

I provide quantitative evidence of the impacts of Prescription Drug Monitoring Programs (PDMPs) on retail opioid prescribing behaviors employing three different identification strategies of difference-in-difference, double selection post-LASSO, and spatial difference-in-difference using county-level high dimensional panel data set from 2010 to 2017. I compare the average retail opioid prescribing behaviors of counties where prescribers abide by state law to check PDMP before prescribing controlled substances (must-access PDMPs) with counties where such a PDMP check is voluntary. I find must-access PDMP reduces about seven retail opioid prescriptions dispensed per 100 persons per year in each county. But, when I compare retail opioid prescribing rates with bordering counties without must-access PDMPs, I find a reduction of three retail opioid prescriptions dispensed per 100 persons per year, suggesting the possibility of spillovers on retail opioid prescribing behaviors and boarder swapping behavior among prescription opioid abusers.

1 Introduction

Overdoses and overdose-deaths related to opioids drugs, including prescription opioid drugs and illicit opioids such as heroin and illicitly manufactured fentanyl, are on the rise in the United States. On average, 130 Americans die every day from an opioid overdose (CDC, 2019). Compared to 1999, prescription-drug sales have quadrupled in the United States (CDC, 2019), leading to a 40 percent increase in prescription drug overdose deaths. As policy responses to the escalating rates of opioid abuse and overdose death rates, the US policymakers have tried a variety of state-level policies[1], however, the CDC has been promoting Prescription Drug Monitoring Program (henceforth PDMP or PDMPs) as the best defense against the current impending crisis Birk and Waddell (2017).

The PDMP allows authorized individuals like doctors, pharmacies, and law enforcement agencies to view a patient's prescription history to facilitate the detection of suspicious prescriptions and utilization behaviors while striking a balance of compassionate care. As of 2019, 49 US states, along with the District of Columbia and the US territory of Guam, have implemented some form of PDMPs. Except for the state of Missouri[2], all the US states have at-least adopted voluntary PDMP. Due to low prescriber use of the systems, few other states have enacted a so-called "mandatory" or "must-access" PDMP. Unlike voluntary PDMP, the must-access PDMP states abide by the law to collect data on controlled substance prescriptions that prescribers have written for patients.

In this paper, I quantify to what extent this "must-access" PDMPs change the opioid prescribing behavior. This research question is a crucial policy-relevant issue because the risk of an opioid use disorder, overdose, and death from prescription opioids are susceptible to the opioid prescribing rate. Several papers relate opioid prescriptions to heroin use and heroin-related crimes (Alpert et al., 2018; Evans et al., 2018; Kilby, 2015; Lankenau et al., 2012; Mallatt, 2018; Meinhofer, 2018). Another strand of literature

[1] Like quantitative prescription limits, patient identification requirements, doctor-shopping restrictions, provisions related to tamper-resistant prescription forms, and pain-clinic regulations (Meara et al., 2016)

[2] St. Louis County that accounts for more than half of Missouri's population, has implemented their unique PDMP and appeal to other counties and cities in Missouri to conjoin (PDMPTTAC, 2019).

relates must-access PDMP to overdosages and overdosages death rates (Buchmueller and Carey, 2018; Meara et al., 2016; Meinhofer, 2018).

However, in this paper, I provide several unique contributions − first, this paper quantifies the impacts of must-access PDMPs on the retail opioid prescribing rate, while several studies exist to answer similar questions (Strickler et al., 2019; Rutkow et al., 2015; Schieber et al., 2019) with descriptive perspectives. See Ponnapalli et al. (2018) for a systematic literature review of PDMPs. In one way, my research resembles Ayres and Jalal (2018) works, where we both are studying the impacts of must-access PDMPs on the retail opioid prescribing rate. However, I propelled toward two unique research directions. First is that I utilize the causal machine learning approach for estimation, and second, is that I provide evidence of cross-border swapping and spillover of prescribing behaviors.

Second, this paper exploits the county level variations of the retail opioid prescribing rate while previous studies provide state-level analysis of PDMPs on various outcomes of interests, and this is because PDMPs are state-level law. However, the county-level analysis offers a more granular summary by capturing the county level heterogeneity on how these state-level PDMP laws change the outcome of interest.

Third, I utilize the two-way fixed effect difference-in-difference econometric approach with two identification strategies using US counties-level high-dimensional panel data ranging from 2010 to 2017. The first approach is the double selection post-LASSO approach − a causal-machine learning method − for variable selection or to select adequate observable characteristics. The second approach exploits spatial contiguity to control for potential unobservables characteristics. This specific approach allows providing quantitative evidence of potential cross-border swapping by abusers and spillover of prescribing behaviors.

The PDMPs are economic policy variables that are not randomly assigned. Therefore several observable characteristics could confound the PDMPs law and opioid prescribing rate. These observable characteristics can be various social, economic, and demographic profiles of counties along with several other state-level laws like Medicaid expansion, marijuana law, good Samaritan law, Naloxone access laws. The double selection post-LASSO within the difference-in-difference framework allows selecting observable controls that affect PDMPs and prescribing rates. I also use state and year level fixed effect to capture state and year specific unobserved heterogeneities; however, this method is likely not to properly handle unobservable characteristics. Hence, under the assumption that the bordering counties are similar in both observables and unobservable characteristics, I compare the prescribing rate among must-access PMDP counties with bordering counties without must-access PMDP.

I find that must-access PDMPs reduce seven retail opioid prescriptions dispensed per 100s persons per county per year. However, when comparing the prescribing rate among must-access PMDP counties with the bordering counties without must-access PMDP, I find about three retail opioid prescriptions dispensed per 100 persons per county per year. Since the prescribing rate in bordering counties is lower than overall counties, it suggests it is likely that the prescribing rate from must-access PDMPs counties spillovers to bordering counties that do not have must-access PDMPs.

Section 2 provides background on opioid epidemic. Section 3 explores the data. Section 4 layouts two-way fixed effect difference-in-difference econometric approach along with the double selection post LASSO, and spatial methods. Section 5 provides the results and section 6 concludes the results.

2 Background

Abuse of prescription opioids drugs is highest compared to other variants of prescription drugs. NSDUH (2014) estimates one in five Americans above 12-year ages misused prescription opioid drugs in their lifetime, and more than one in four new initiates of illicit drug users started with prescription opioid drug abuse. About 119 million Americans aged 12 or older used prescription psychotherapeutic drugs in the past year, representing 44.5

percent of the population. And about 18.9 million people aged 12 or older (7.1 percent) misused prescription psychotherapeutic drugs in the past year. NSDUH (2015) highlights several contributing factors to the prescription opioid drug epidemic, namely the advancement of new drug therapies, prescribing practices, internet pharmacies, expansion of insurance coverage, pharmaceutical advertisement, increased availability, medication and prescription pad theft, employee pilferage.

Opioid-dependent abusers steal, street purchase from a friend or relative, and doctor-shop to obtain prescription opioid drugs for non–medical use. Physicians represent the primary source for prescription opioid opioids for those who obtain prescription opioids through their own prescriptions Jones et al. (2014). In contrast, pharmacists and physicians claim doctor shopping as the leading source for opioid abusers to get prescription opioid opioids (NSDUH, 2015) and is an indirect channel of supply source for street dealers (Inc, 2009).

As policy responses to the escalating rates of opioid abuse and overdose death rates, the US policymakers have tried a variety of state-level policies like quantitative prescription limits, patient identification requirements, doctor-shopping restrictions, Prescription Drug Monitoring Program (henceforth PDMP or PDMPs), provisions related to tamper-resistant prescription forms, and pain-clinic regulations (Meara et al., 2016). The CDC has been promoting PDMPs as the best defense against the current impending crisis Birk and Waddell (2017). However, the PDPMs varies by state along several dimensions[3] and also evolve over time.[4]

Differentiating among voluntary and must-access PDMPs is crucial to understand how these programs affect the prescribing rate. For example, when New York implemented a must-access PDMP in 2013, the number of registrants increased fourteen-fold, and the

[3]States can differ in who may access the database (e.g., prescribers, dispensers, law enforcement), in the agency that administers the PDMP (e.g., department of health, pharmacy boards), in the controlled substances (CS) that are reported (e.g., some do not monitor CS-V), in the timeliness of data reporting (e.g., daily, weekly), in how to identify and investigate cases of potential doctor shoppers (e.g., reactive, proactive), and on whether prescribers are required to query the database (Meinhofer, 2018).

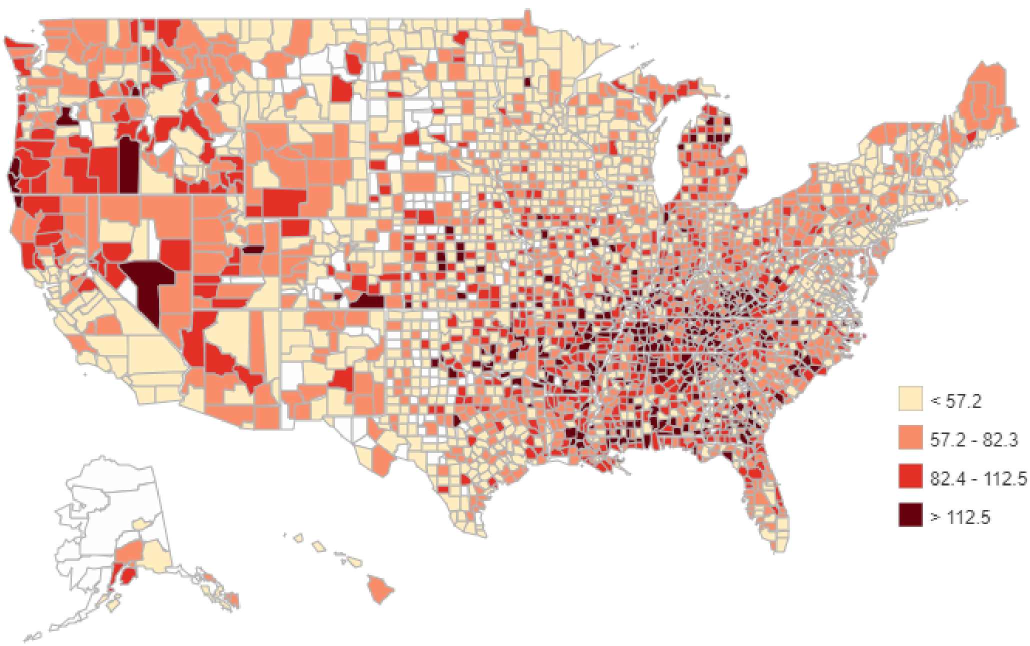
[4]Initially, several states implemented paper-based PDMPs. Still, eventually, these and others shifted to electronic-based PDMPs (Meinhofer, 2018).

number of daily queries rose from fewer than 400 to more than 40,000 (PDMP Center of Excellence, 2016). Similarly, in Kentucky, Tennessee, and Ohio, implementing a "must access" provision increased by order of magnitude the number of providers registered and the number of queries received per day. In contrast, in the first year after a voluntary PDMP was established in Florida, a state with a well-publicized opioid misuse problem, fewer than one in ten physicians had even created a login for the system (Electronic-Florida Online Reporting of Controlled Substances Evaluation, 2014).

3 Data

I web-scrape CDC website to acquire data of the retail opioid prescriptions dispensed per 100 persons per year[5] from 2006 to 2017. CDC estimates prescribing rates using the IQVIA Xponent data set.

Figure 1: Retail Opioid Dispensed per 100 Persons per Year, 2017



Source: https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html

IQVIA Xponent is based on a sample of approximately 50,000 retail (non-hospital)

[5]Note that retail opioid prescriptions dispensed per 100 persons per year index is different from the morphine milligram equivalent (MME) per person or the number of opioids prescribed per person.

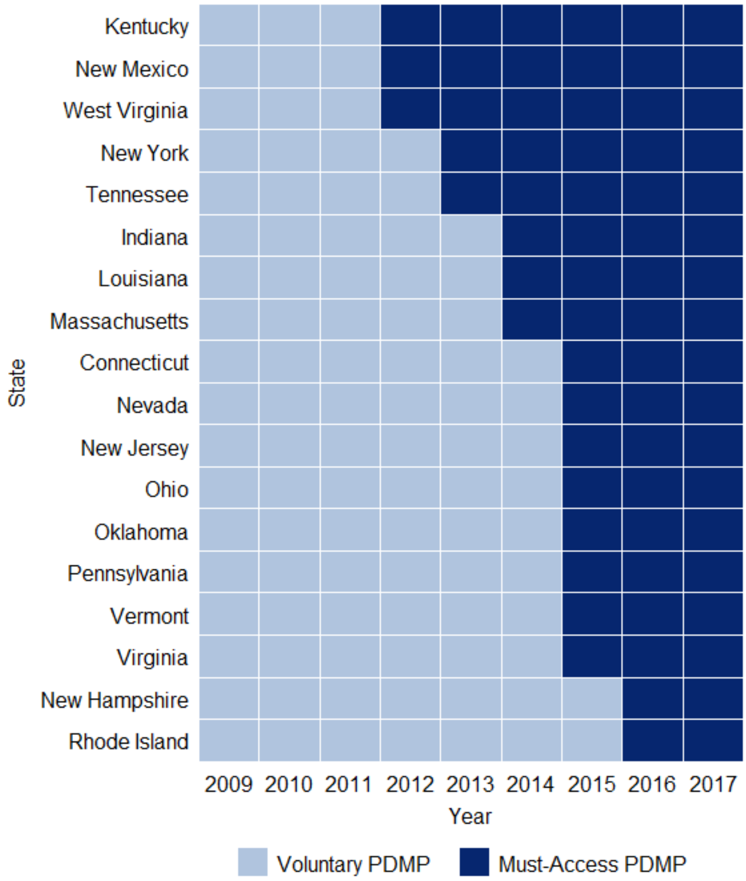
pharmacies, which dispense nearly 90% of all retail prescriptions in the United States. For this database, a prescription is an initial or refill prescription dispensed at a retail pharmacy in the sample and paid for by commercial insurance, Medicaid, Medicare, or cash or its equivalent. This database does not include mail order pharmacy data. IQVIA Xponent data set uses the National Drug Code to identify opioid prescriptions, which include buprenorphine, codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, propoxyphene, tapentadol, and tramadol. However, the IQVIA Xponent data set excludes cough and cold formulations containing opioids and buprenorphine products typically used to treat opioid use disorder. In addition, methadone dispensed through methadone maintenance treatment programs is not included in the IQVIA Xponent data. A lack of available data in IQVIA Xponent may indicate that the county had no retail pharmacies, the county had no retail pharmacies sampled, or the prescription volume was erroneously attributed to an adjacent, more populous county according to the sampling rules used.

I retrieve the list of states that require prescribers to check the PDMP before prescribing controlled substances or must-access PDMP and the PDMP enactments date from the pdaps.org website. Figure 2 is a visual representation of the state and timing of states that enacted must-access PDMP and the state with only voluntary PMDPs.

Using the Application Programming Interface of Census from the "censusapi" R package, I retrieve all the social, economic, housing, and demographic data profile of each county in the US from the five-year American Community Survey from 2010 to 2017. Then, I only include variables that are consistently available from 2010 to 2017. I then deleted variables that are a linear combination of each other and remove highly correlated variables. At last, this process retains 90 different social, economic, housing, and demographic data profile of each county.

I also retrieve state-level laws like Good Samaritan Laws and Naloxone Access Law from the pdaps.org website. I use procon.org to access the Marijuana Law (medical or/and recreational possession of Marijuana). States with the Good Samaritan Law

Figure 2: State requiring prescribers to check the PDMP before prescribing controlled substances.



Source: http://pdaps.org/

provide immunity from prosecution for possessing a controlled substance while seeking help for himself or another person experiencing an overdose. The state with Naloxone Access Law provides naloxone and other opioid overdose prevention services to individuals who use drugs, their families and friends, and service providers, including education about overdose risk factors, signs of overdose, appropriate response, and administration of naloxone. As of 2016, 48 states have authorized some variant of a naloxone access law, and 37 states have passed a drug overdose good samaritan law (Ayres and Jalal, 2018).

4 Methodology

4.1 Difference-in-Difference with Fixed Effects

I begin the analysis by showing if there is a significant difference in retail opioid prescriptions dispensed per 100 persons between the counties of the state that have a must-access PDMP with the counties of the state that don't have such a program. For this, I use a difference-in-difference model with county and year fixed effects.

$$Y_{it} = c + \delta D_{it} + \alpha_i + \varsigma_t + \varepsilon_{it} \tag{1}$$

where, Y_{it} is retail opioid prescriptions dispensed per 100 persons per year; c is the intercept, D_{it} is the treatment indicator and equals 1 after state i has been exposed to the treatment (must-access PDMP) and equals 0 otherwise; δ is the average treatment effect, α_i and ζ_t are additive individual state and year fixed effects respectively. One should expect a negative and significant value of δ, which would suggest the PDMP is successful in reducing retail opioid prescriptions dispensed. However, a positive and significant δ shows that state with PDMP have, on average higher retail opioid prescriptions dispensed rates compare to comparison states that do not have must-access PDMP.

4.2 High Dimensional Features and Unknown Data Generating Process

Studies that examine the impact of the must-access PDMPs on the retail opioid prescriptions dispensed are likely to suffer the endogeneity. The endogeneity leads to either over or underestimating the effects of must-access PDMPs on the retail opioid prescriptions dispensed. The endogeneity arises because must-access PDMP enactment is a policy response to the escalating opioid-related overdose death rate and opioid prescribing behavior.

The equation (1) produces an incomplete picture of the relationship between retail opioid prescriptions dispensed and must-access PDMP. Since the policy/treatment variable is PDMP is a non-randomly assigned economic variable. The socio-economic and demographic profile of each county could likely affect both retail opioid prescriptions and must-access PDMP. Furthermore, literature has shown that Medicaid expansion, marijuana law, good Samaritan law, Naloxone access laws have a diverse effect on the demand for prescription opioids.

Failure to conditioning these confounders can lead to omitted variable bias. However, over-controlling leads to loss of efficiency of estimates. The actual data generating a process that explains the relationship between the must-access PDMPs and the opioid prescribing rate is unknown to the researcher. However, one can use general economic intuition to guide the variable selection that is standard in the literature. However, the actual data generating process (DGP) might comprise the various transformation of these observable confounders, for example, lags, higher-order polynomials, and interactions. Including and controlling for all these transformations may not be feasible because the covariates space can increase exponentially with high dimensional data.

Hence, the primary goal is to inference the low-dimensional parameter from the high-dimensional nuisance parameter, which comprises to solve auxiliary prediction problem quite well. Consider the following outcomes y_i as a partially linear model:

$$\begin{aligned} y_i = d_i\alpha_0 + g\left(z_i\right) + \xi_i, \quad E\left[\xi_i | z_i, d_i\right] = 0 \\ d_i = m\left(z_i\right) + v_i, \quad E\left[v_i | z_i\right] = 0 \end{aligned} \tag{2}$$

where we have a sample of $i = 1, \ldots, n$ independent observation, d is policy/treatment variable as "must-access" PDMPs possibly non-randomly assigned an economic variable. The α_0 is the target parameter of interest, which answers the portion of variations in outcome variable due to the changes in policy variables. z_i is a high-dimensional vector of other controls or confounders. The high-dimensional vector of controls is in z_i and collected from the social, economic, housing, and demographic data profile from the American Community Survey for each county from 2010 to 2017. It is plausible to define that some of those features are a common cause for the existence of "must-access" PDMP and opioid prescription, and $m_0 \neq 0$, typically in the case of observational studies. $m_0 = 0$ would suggest that the policy variable is randomly assigned.

4.3 Double Selection Post LASSO

Lets consider linear combinations of control terms $x_i = P(z_i)$ to approximate $g(z_i)$ and $m(z_i)$. The list $x_i = P(z_i)$ could be composed of many transformations of elementary regressors z_i such as B-splines, dummies, polynomials, and various interactions. Having many controls poses a challenge of estimation and inference, therefore, to avoid such we assume the sparsity assumption that only a few among many variables in the z_i explains outcomes y_i.

$$\begin{aligned} y_i &= d_i\alpha_0 + \underbrace{x'_i\beta_{g0} + r_{gi}}_{g(z_i)} + \xi_i \\ d_i &= \underbrace{x'_i\beta_{m0} + r_{mi}}_{m(z_i)} + v_i \end{aligned} \tag{3}$$

The sparsity then relates to $x'_i\beta_{g0}$ and $x'_i\beta_{m0}$ approximate $g(z_i)$, and $m(z_i)$ that requires only a small number of non-zero coefficients to render corresponding approximation errors r_{gi} and r_{mi}.

An appealing method to estimate the sparse parameter from a high-dimensional linear model is the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996). LASSO simultaneously performs model selection and coefficient estimation by minimizing the sum of squared residuals plus a penalty term. The penalty term penalizes the size of the model through the sum of absolute values of coefficients.

Let me define a feasible variable selection via LASSO for outcome variable and policy or treatment variable. Here, we change the notation as the outcome, and the policy variable takes the following form:

$$\begin{aligned}\tilde{y}_i &= \underbrace{x_i\beta_1 + r_i +}_{f(\tilde{z}_i)} \varepsilon_i \\ \tilde{d}_i &= \underbrace{x_i\beta_2 + m_i +}_{f(\tilde{z}_i)} \varepsilon_i\end{aligned} \tag{4}$$

moreover, LASSO estimator is defined as the solution to:

$$\begin{aligned}\min_{\beta_1 \in \mathbb{R}^p} E_n\left[(\tilde{y}_i - \tilde{x}_i\beta_1)^2\right] + \frac{\lambda}{n}\|\beta_1\|_1 \\ \min_{\beta_2 \in \mathbb{R}^p} E_n\left[\left(\tilde{d}_i - \tilde{x}_i\beta_2\right)^2\right] + \frac{\lambda}{n}\|\beta_2\|_1\end{aligned} \tag{5}$$

where, the penalty level λ is a tuning parameter to regularize/controls the degree of penalization and to guard against overfitting. We choose λ by cross-validation in prediction. The $\|\beta\|_1 = \sum_{j=1}^{p} |\beta_j|$. The kinked nature of penalty function induces $\hat{\beta}$ to have many zeros, thus LASSO solution feasible model selection method. The estimated coefficients are biased towards 0; therefore, Belloni et al. (2013) and Belloni et al. (2014) suggest to run an OLS on selected variables also known as post-LASSO or Gauss-LASSO estimator.

Let $\hat{I}_1 = S\left(\hat{\beta}_1\right)$ denote support or the controls selected by feasible LASSO estimator $\hat{\beta}_1$ and $\hat{I}_2 = S\left(\hat{\beta}_2\right)$ denote support or the controls selected by feasible LASSO estimator $\hat{\beta}_2$. The post-double-selection estimator $\breve{\alpha}$ of α_0 is defined as the least squares estimator obtained by regressing y_i on d_i and the selected control terms x_{ij} with $j \in \hat{I} \supseteq \hat{I}_1 \cup \hat{I}_2$:

$$\left(\breve{\alpha}, \breve{\beta}\right) = \min_{\alpha \in \mathbb{R}, \beta \in \mathbb{R}^p} E_n\left[(y_i - d_i\alpha - \tilde{x}_i\beta)^2\right] \quad : \quad \beta_j = 0, \forall j \notin \hat{I} \tag{6}$$

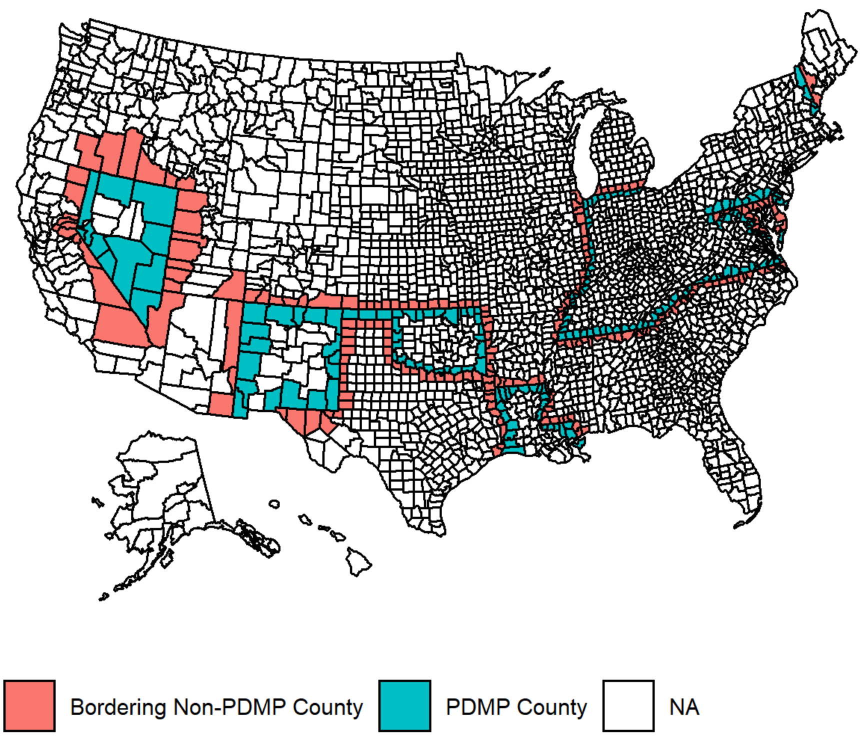
In this equation (6), we can impose fixed effects and we can also cluster standard error. Belloni et al. (2013) provide theoretical results that the estimates are unbiased and consistent as:

$$\left(\left[\tilde{E}\tilde{v}_i^2\right]^{-1} E\left[\tilde{v}_i^2\tilde{\xi}_i^2\right]^{-1}\left[\tilde{E}\tilde{v}_i^2\right]^{-1}\right)^{-1/2} \sqrt{n}\left(\breve{\alpha} - \alpha_0\right) \xrightarrow{d} N(0,1) \tag{7}$$

4.4 Managing Unobservable with Spatial Difference-in-Difference

The equation (6) allows us to properly select few or sparse observables from the high dimensional observables that could affect both the outcomes and policy variables. Equation (6) can utilize fixed effects to handle unobserved heterogeneity. However, as an additional layer of caution, I exploit the county level spatial contiguity. Rather than comparing outcomes of all the counties within the state with PDMPs and without PDMPs, in this setting, I implement equation (1) and (6) to compare outcome variables from the neighboring PDMPs county with the bordering counties without PDMPs. Figure (3) exhibits a map of the US that comprises the bordering treatment and comparison counties in a different color for the year 2017.

Figure 3: Bordering Counties, 2017



5 Results

Table 1 show the impacts of PDMP on retail opioid prescriptions dispensed with the Naïve OLS, double selection post-LASSO with pooled OLS, Naïve fixed effect, and double selection post-LASSO with fixed effect model in column (1) to (4) respectively. The dependent variable is retail opioid prescriptions dispensed per 100 persons, and the policy variable is the must-access PDMP. The standard errors are clustered at the state level to account for the intra-state level correlations.

Table (1) column (1) and (2) are estimates of Naïve OLS and double selection post-LASSO with pooled OLS. These estimates are not signification in a 5% level of significance. However, the Naïve OLS model's intercept holds the interpretation that, on average, in non-PDMPs counties, retail opioid prescriptions dispensed per 100 persons is 83, and counties with must-access PDMPs on average have additional six retail opioid prescriptions dispensed per 100 persons. For the remaining models in Table (1) column (2) to (4), the intercepts are not interpretive; therefore, I do not report them.

Table 1: Impacts of must-access PDMP on Retail Opioid Prescriptions Dispensed

	Retail opioid prescriptions dispensed per 100 persons			
	Naïve OLS (1)	Pooled OLS (2)	Naïve FE (3)	DSPL FE (4)
PDMP	6.210	-2.622	-7.572***	-6.882***
	(7.064)	(3.282)	(2.035)	(1.521)
Intercept	83.530***			
	(3.535)			
R^2	0.002	0.258	0.929	0.931
$Adj\text{-}R^2$	0.002	0.257	0.919	0.920
County FE			Y	Y
Year FE			Y	Y
DSPL		Y		Y

Notes: Note: Robust standard errors clustered by the state are reported in parenthesis. *, ** and *** represent the 10%, 5% and 1% level of significance. Double selection post-LASSO (DSPL) is used for covariates selection. FE represents fixed effects.

Table (1), column (3) and (4) estimate Naïve fixed effect and double selection post LASSO with fixed-effect models. Both models suggest that a reduction of 7 retail opioid prescriptions dispensed per 100 persons in the counties with must-access PDMPs compared to comparison counties. The estimates of column (3) and (4) are similar; therefore, to save space, I do not report the selected variables.

Table 2: Impacts of must-access PDMP on Retail Opioid Prescriptions Dispensed, Spatial Contiguity

	Retail opioid prescriptions dispensed per 100 persons			
	Naïve OLS (1)	Pooled OLS (2)	Naïve FE (3)	DSPL FE (4)
PDMP	-9.184***	-2.426	-1.974	-3.158*
	(2.917)	(4.088)	(1.374)	(1.799)
Intercept	95.975***			
	(6.671)			
Good Samaritan Law				9.035***
				(2.882)
Information Industry (%)				3.811**
				(1.679)
Construction Industry (%)				1.032*
				(0.528)
Commuting Worked at Home (%)				-1.336*
				(0.665)
R^2	0.009	0.406	0.932	0.935
$Adj\text{-}R^2$	0.008	0.403	0.922	0.925
County FE			Y	Y
Year FE			Y	Y
DSPL		Y		Y
Selected covariates				Y

Notes: Note: Robust standard errors clustered by the state are reported in parenthesis. *, ** and *** represent the 10%, 5% and 1% level of significance. Double selection post-LASSO (DSPL) is used for covariates selection. FE represents fixed effects.

Contrary to Table (1), in Table (2), I consider the must-access PDMP state's counties' retail opioid prescription rate with bordering counties from the state that have not enacted must-access PDMPs. Under the assumption that these bordering counties would be similar in their unobservables, I can test the impacts of must-access PDMPs on the retail opioid prescription rate. This will also allow checking if retail opioid prescription rate spillovers from must-access PDMPs counties to bordering counties without must-access PDMPs.

Table (2), column (1) presents estimates of Naïve OLS. The intercept shows that non-must-access PDMPs state counties bordered with must-access PDMPs state counties have 95 retail opioid prescription rates per 100 persons, which is about nine retail opioid prescription rates per 100 persons higher.

Table (2), column (2), and (3) estimates Pooled OLS where the controls are selected using double selection post-LASSO and a Naive fixed effects estimate, respectively. Both these estimates show an insignificant effect of must-access PDMPs on the retail opioid prescription rate. However, the double selection post-LASSO with fixed effect in column (4) shows a reduction of about three retail opioid prescriptions rate per 100 persons, and this model selects several variables.

I choose and put only the significant control variables in column (4) to save space. Compared to counties without Good Samaritan Law, the counties with Good Samaritan Law have about nine more retail opioid prescription rates per 100 persons. States with the Good Samaritan Law provide immunity from prosecution for possessing a controlled substance while seeking help for himself or another person experiencing an overdose. Counties with a higher share of information and construction industry experience an additional 4 and 1 more retail opioid prescription rate per 100 persons, whereas counties with a higher share population who worked from home and did not commute have about one less retail opioid prescription rate per 100 persons.

6 Conclusion

This study quantifies how does the must-access PMDPs affect the retail prescription opioid prescribing rate and presents first-hand evidence at the county-level. Compare to non-must-access PDMPs counties, the must-access PDMPs counties, on average, have seven less retail opioid prescriptions dispensed per 100 persons per year. But, when I compare the bordering counties only, to control unobservables, I find must-access PDMPs counties have three less retail opioid prescriptions dispensed per 100 persons per year compared to their bordering counterpart non-must-access PDMPs counties, suggesting the possibilities of spillovers of retail opioid prescribing behaviors.

This study raises several issues. First, how much such a reduction of retail opioid prescriptions dispensed per 100 persons per year translates into the decline of the prescription-related opioid death rate. Although the number of opioid-related deaths from all sources increased since 2012, the number of deaths each year associated with the use of prescription opioids alone has not increased since then (Schieber et al., 2019). Similarly, a reduction in retail opioid prescriptions could lead opioid abusers to switch toward other substitutes that are cheaper and illicit. If there exists such substitution, then there could be unintended consequences of must-access PDMPs like increase crime, opioid poisoning, and deaths related to illegally manufactured Fentynal or heroine. Therefore, to solve the current opioid epidemic, both illicit street drugs and prescription opioids must become less available without compromising the need to compensate medical care related to the opioid and get patients with opioid use disorder into treatment.

This study is subject to several limitations. CDC's IQVIA Xponent data set uses the National Drug Code to identify opioid prescriptions, which include buprenorphine, codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, propoxyphene, tapentadol, and tramadol. Each of these drugs is likely not equally prescribed; therefore, without administrative IQVIA Xponent data set, it is not possible to see the heterogeneities within the retail prescription opioid prescribing rate. Furthermore, each must-access PDMPs can be different stringent on several dimensions. For example, states can differ in who may access the database (e.g., prescribers, dispensers, law enforcement), in the agency that administers the PDMP (e.g., department of health, pharmacy boards), in the controlled substances (CS) that are reported (e.g., some do not monitor CS-V), in the timeliness of data reporting (e.g., daily, weekly), in how to identify and investigate cases of potential doctor shoppers (e.g., reactive, proactive), and on whether prescribers are required to query the database (Meinhofer, 2018). This study doesn't account for such variability of stringent PDMPs.

The analysis presented in this paper may inform states as they create laws, policies, communications, and interventions tailored to their specific problems. The magnitude, severity, and chronic nature of the opioid epidemic in the United States are of serious concern to clinicians, the government, the general public, and many others. As they review new studies and recommendations, clinicians should continue to consider how they might improve pain management, including opioid prescribing, in their practice (Schieber et al., 2019).

References

(2009). Prescription Opioid Abuse and Diversion in an Urban Community: The Results of an Ultra–Rapid Assessment. *Pain Medicine*, 10(3):537–548.

Alpert, A., Powell, D., and Pacula, R. L. (2018). Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids. *American Economic Journal: Economic Policy*, 10(4):1–35.

Ayres, I. and Jalal, A. (2018). The Impact of Prescription Drug Monitoring Programs on U.S. Opioid prescriptions. *Journal of Law, Medicine and Ethics*, 46(2):387–403.

Belloni, A., Chernozhukov, V., and Hansen, C. (2013). Inference on Treatment Effects After Selection Among High-dimensional Controls. *Review of Economic Studies*, 81(2):608–650.

Belloni, A., Chernozhukov, V., and Hansen, C. (2014). High-Dimensional Methods and Inference on Structural and Treatment Effects. *Journal of Economic Perspectives*, 28(2):29–50.

Birk, E. and Waddell, G. R. (2017). The Mitigating Role of Prescription Drug Monitoring Programs in the Abuse of Prescription Drugs.

Buchmueller, T. C. and Carey, C. (2018). The Effect of Prescription Drug Monitoring

Programs on Opioid Utilization in Medicare. *American Economic Journal: Economic Policy*, 10(1):77–112.

CDC (2019). Understanding the Epidemic — Drug Overdose — CDC Injury Center.

Electronic-Florida Online Reporting of Controlled Substances Evaluation (2014). 2011–2012 Prescription Drug Monitoring Program Annual report. florida Department of Health. Tallahassee, December.

Evans, W. N., Lieber, E. M., and Power, P. (2018). How the Reformulation of OxyContin Ignited the Heroin Epidemic. *The Review of Economics and Statistics*, page rest_a_00755.

Jones, C., Paulozzi, L., and Mack, K. (2014). Sources of Prescription Opioid Pain Relievers by Frequency of Past-year Nonmedical use: United states, 2008-2011. *JAMA Internal Medicine*, 174(5):802–803.

Kilby, A. (2015). Opioids for the Masses: Welfare Tradeoffs in the Regulation of Narcotic Pain Medications. *Working Paper*.

Lankenau, S. E., Teti, M., Silva, K., Bloom, J. J., Harocopos, A., and Treese, M. (2012). Initiation into Prescription Opioid Misuse amongst Young Injection Drug Users. *International Journal of Drug Policy*.

Mallatt, J. (2018). The Effect of Prescription Drug Monitoring Programs on Opioid Prescriptions and Heroin Crime Rates. *SSRN*.

Meara, E., Horwitz, J. R., Powell, W., McClelland, L., Zhou, W., O'Malley, A. J., and Morden, N. E. (2016). State Legal Restrictions and Prescription-Opioid Use among Disabled Adults. *New England Journal of Medicine*, 375(1):44–53.

Meinhofer, A. (2018). Prescription Drug Monitoring Programs: The Role of Asymmetric Information on Drug Availability and Abuse. *American Journal of Health Economics*, 4(4):504–526.

NSDUH (2014). Prescription Drug Use and Misuse in The United States: Results from the 2014 National Survey on Drug Use and Health. NSDUH Data Review, Substance Abuse and Mental Health Services Administration.

NSDUH (2015). Prescription Drug Use and Misuse in The United States: Results from the 2015 National Survey on Drug Use and Health. NSDUH Data Review, Substance Abuse and Mental Health Services Administration.

PDMP Center of Excellence (2016). PDMP prescriber use mandates: characteristics, current status, and outcomes in selected states.

PDMPTTAC (2019). Prescription Drug Monitoring Frequently Asked Questions (FAQ) The PDMP Training and Technical Assistance Center.

Ponnapalli, A., Grando, A., Murcko, A., and Wertheim, P. (2018). Systematic Literature Review of Prescription Drug Monitoring Programs. *Annual Symposium proceedings. AMIA Symposium*, 2018:1478–1487.

Rutkow, L., Chang, H.-Y., Daubresse, M., Webster, D. W., Stuart, E. A., and Alexander, G. C. (2015). Effect of Florida's Prescription Drug Monitoring Program and Pill Mill Laws on Opioid Prescribing and Use. *JAMA Internal Medicine*, 175(10):1642–1649.

Schieber, L. Z., Guy, Gery P., J., Seth, P., Young, R., Mattson, C. L., Mikosz, C. A., and Schieber, R. A. (2019). Trends and Patterns of Geographic Variation in Opioid Prescribing Practices by State, United States, 2006-2017. *JAMA Network Open*, 2(3).

Strickler, G. K., Zhang, K., Halpin, J. F., Bohnert, A. S., Baldwin, G. T., and Kreiner, P. W. (2019). Effects of Mandatory Prescription Drug Monitoring Program (PDMP) Use Laws on Prescriber Registration and Use and on Risky Prescribing. *Drug and Alcohol Dependence*, 199:1–9.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1):267–288.