

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

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Abstract

Based on 2010 to 2017 county-level high dimensional panel data set, this paper provides first-hand quantitative evidence on how much Prescription Drug Monitoring Programs (PDMPs) changes the retail opioid prescribing behaviors. For this, I use three different identification strategies: difference-in-difference, double selection post-LASSO, and spatial difference-in-difference. I compare the retail opioid prescribing behaviors of counties from a state requiring prescribers to check the PDMP before prescribing controlled substances (must-access PDMPs) with the counties of states where such a PDMP check is voluntary. I find must-access PDMPs reduces about seven retail opioid prescriptions dispensed per 100 persons per year in each county. But, when I compare must-access PDMPs counties with bordering counties without such law, I find a reduction of three retail opioid prescriptions dispensed per 100 persons per year suggesting the possibility of spillovers of retail opioid prescribing behaviors.

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1 Introduction

Deaths related to overdoses of opioids drugs, including both prescription opioid drugs and illicit opioids such as heroin and illicitly manufactured fentanyl, are rising in the United States, especially after 2010. 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 leading to a 40 percent increase in prescription drug overdose deaths.

Abuse of prescription opioids drugs is highest compared to other variants of prescription drugs. National Center on Addiction and Substance Abuse (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. National Center on Addiction and Substance Abuse (2015) estimates 119 million Americans aged 12 or older used prescription psychotherapeutic drugs in the past year, representing 44.5 percent of the population and 18.9 million people aged 12 or older (7.1 percent) misused prescription psychotherapeutic drugs in the past year. National Center on Addiction and Substance Abuse (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 (National Center on Addiction and Substance Abuse, 2015) and is an indirect channel of supply source for street dealers (Inciardi et al., 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).

As of 2019, 49 US states, along with the District of Columbia and the US territory of Guam has implemented some form of PDMPs. Except for the state of Missouri¹, all the US states have adopted voluntary PDMP. In contrast, few other states have enacted a so-called “mandatory” or must-access

¹St. Louis County that accounts for more than half of the population of Missouri have implemented their unique PDMP and appeal to other counties and cities in Missouri to conjoin (PDMPTTAC, 2019).

PDMP. Unlike voluntary PDMP, the must-access PDMP states abide by the law to collect data on controlled substance prescriptions that doctors have written for patients. The must-access PDMP states allow authorized individuals to view a patient’s prescription history to facilitate the detection of suspicious prescriptions and utilization behaviors. The PDMPs varies by state along several dimensions² and also evolve over time³.

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 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 (PDMP Center of Excellence, 2016). 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).

In this paper, I am quantifying to what extent these 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 the reduction of an opioid prescription to heroin crime (Alpert et al., 2017; Evans et al., 2018; Kilby, 2015; Lankenau et al., 2012; Mallatt, 2018; Meinhofer, 2018b). While another strand of literature relates must-access PDMP to overdoses and overdoses death rates (Buchmueller and Carey, 2018; Meara et al., 2016; Meinhofer, 2018b). However, in this paper, I provide several unique contributions – first, this paper study of impacts of must-access PDMPs on the retail opioid prescribing rate. Several studies exist to answer similar questions (Strickler et al., 2019; Rutkow et al., 2015; Schieber et al., 2019) but these studies are descriptive. See Ponnappalli et al. (2018) for systematic literature review of Prescription Drug Monitoring Programs too. However, I contribute to quantifying the impacts of must-access PDMPs on the opioid prescribing rate.

Second, this paper is first to exploit the county level variations of the retail opioid prescribing rate. Several 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

²States 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, 2018a).

³Initially, several states implemented paper-based PDMPs. Still, eventually, these and others shifted to electronic-based PDMPs (Meinhofer, 2018a).

interest.

Third, I also utilize the two-way fixed effect difference-in-difference econometric approach with two novel identification strategy using US counties-level panel data that span from 2010 to 2017. The first approach is the double selection post-LASSO – a causal-machine learning method – to control observable characteristics. The second approach exploits spatial contiguity to control for unobservables characteristics, possibly. The PDMPs are economic policy variables that are likely not to be randomly assigned. Therefore several observable characteristics could confound the PDMPs law and opioid prescribing rate. These observable characteristics can be the 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 allows selecting observable controls that affect PDMPs and prescribing rates. However, this method is likely not to properly unobservable. I compare the prescribing rate among must-access PMDP counties, which the 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, which the bordering counties without must-access PMDP, I find about three retail opioid prescriptions dispensed per 100s persons per county per year. Since the prescribing rate in boarding 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 explores the data. Section 3 layouts two-way fixed effect difference-in-difference econometric approach along with the double selection post LASSO and spatial methods. Section 4 provides the results and section 5 concludes the results.

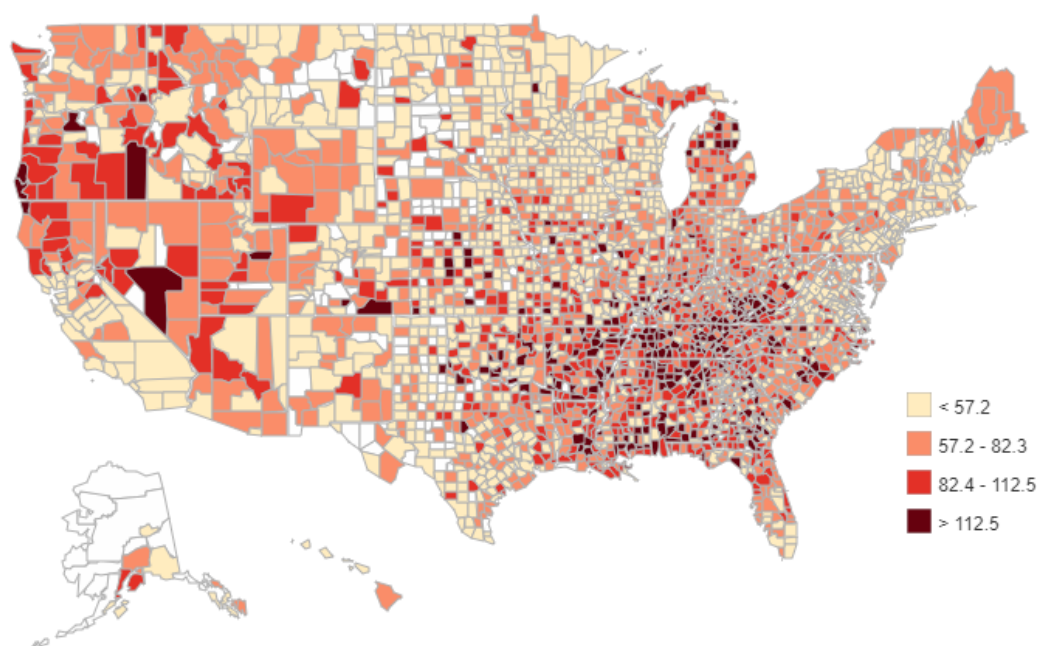
2 Data

I web-scrape CDC website to acquire data of the retail opioid prescriptions dispensed per 100 persons per year⁴ from 2006 to 2017. CDC estimates prescribing rates using the IQVIA Xponent data set.

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

⁴Note 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.

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



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

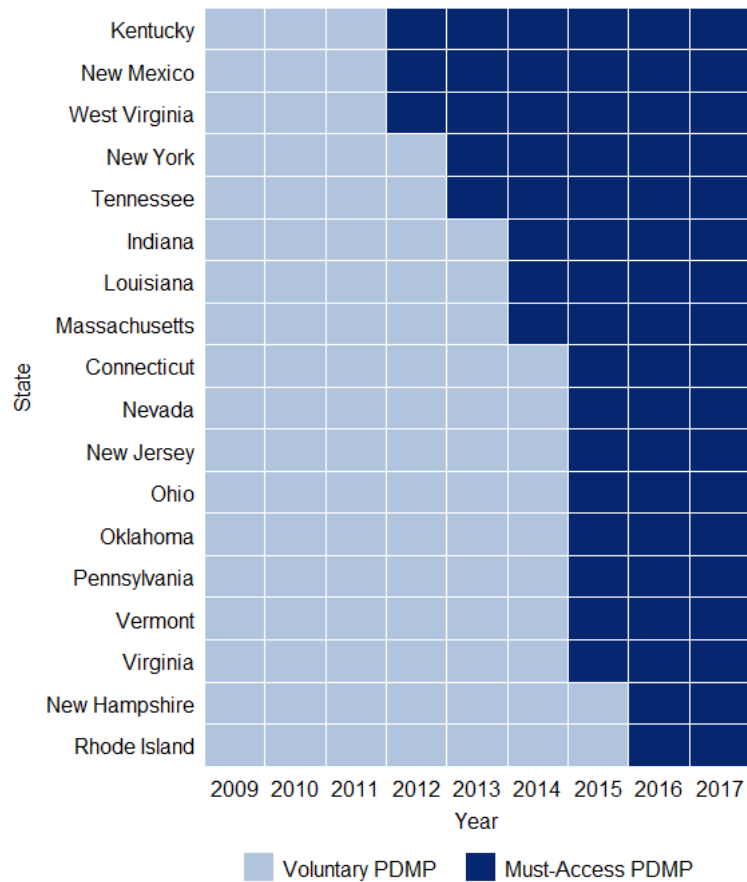
oxycodone, oxymorphone, propoxyphene, tapentadol, and tramadol. However, the IQVIA Xponent data set excludes cough and cold formulations containing opioids and buprenorphine products that are typically used to treat opioid use disorder. In addition, methadone dispensed through methadone maintenance treatment 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.

For the calculation of prescribing rates, numerators are the total number of opioid prescriptions dispensed in a county in a given year, and the denominator is the annual resident population denominator estimates obtained from the US Census Bureau. Figure (1) shows US opioid prescribing rate maps in 2017, where rates are classified by the Jenkse natural breaks classification method into four groups using the 12-year range of data (2006 to 2017) to determine the class breaks.

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 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

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



Source: <http://pdaps.org/>

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 also remove furthermore highly correlated variables. This process, at last, 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 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 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).

3 Methodology

3.1 Difference-in-Difference with Fixed Effects and clustered Standard-Errors

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 prescription drug monitoring program (PDMPs henceforth) with the counties of the state that don't have such program. For this, I use a simple difference-in-difference model with county and year fixed effects while clustering the standard errors in-state levels.

$$Y_{it} = c + \delta D_{it} + \alpha_i + \zeta_t + \varepsilon_{it} \quad (1)$$

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.

3.2 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 underestimation of 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:

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

where we have a sample of $i = 1, \dots, n$ 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.

3.3 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:

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

moreover, LASSO estimator is defined as the solution to:

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

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 $\hat{I}_1 = S(\hat{\beta}_1)$ denote support or the controls selected by feasible LASSO estimator $\hat{\beta}_1$ and $\hat{I}_2 = S(\hat{\beta}_2)$ denote support or the controls selected by feasible LASSO estimator $\hat{\beta}_2$. The post-double-selection estimator $\tilde{\alpha}$ 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 $j \in \hat{I} \supseteq \hat{I}_1 \cup \hat{I}_2$:

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

In this equation (6), we can impose fixed effects and we can also cluster standard error. Belloni et al.

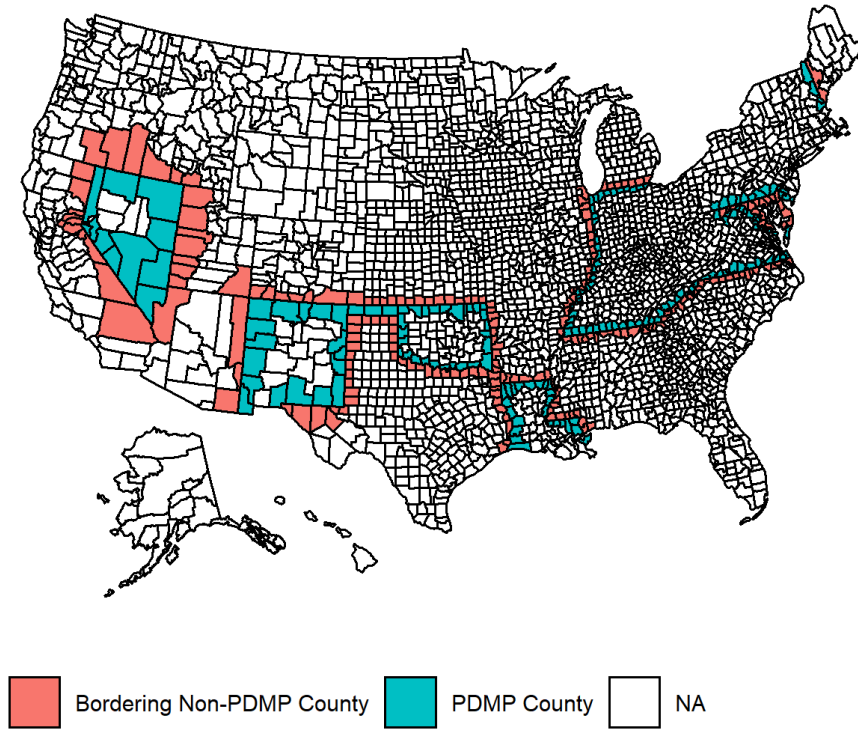
(2013) provide theoretical results that the estimates are unbiased and consistent as:

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

3.4 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



4 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 significant in a 5% level of significance. However, the intercept of the Naïve OLS model 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 interpretable; 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 (7.064)	-2.622 (3.282)	-7.572*** (2.035)	-6.882*** (1.521)
Intercept	83.530*** (3.535)			
R^2	0.002	0.258	0.929	0.931
$Adj-R^2$	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.

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

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*** (2.917)	-2.426 (4.088)	-1.974 (1.374)	-3.158* (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
$Adj-R^2$	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.

must-access PDMPs.

Table (2), column (1) presents estimates of Naïve OLS. The intercept shows that non-must-access PDMPs state counties that 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 Naïve 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 has about nine more retail opioid prescription rate 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.

5 Conclusion

This study quantifies how does the must-access PDMPs 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 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, 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 Fentanyl or heroine. Therefore, to solve the current opioid epidemic, both illicit street drugs and prescription opioids must become less available without compromising the need for compensating medical care related to the opioid and getting 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, 2018a](#)).

This study doesn't account for such variability of stringent PDMPs.

The analysis presented in this paper may be able to 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 is 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).

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