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# Impact of Prescription Drug Monitoring Program on Drug Misuse and Drug-related Fatal Vehicle Crashes

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**TITLE PAGE**

# Impact of Prescription Drug Monitoring Program on Drug Misuse and Drug-related Fatal Vehicle Crashes

by

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I dedicate this dissertation to my family for their unconditional affection, love, and support.

تقدیم به پدر و مادرم

که وجودم برایشان همه رنج بود و وجودشان برایم همه مهر

## ABSTRACT

**Impact of Prescription Drug Monitoring Program on Drug Misuse and Drug-related Fatal Vehicle Crashes**

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University of Nebraska, 2021

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Over the last two decades, prescription drug use increased across the U.S. and was associated with a corresponding rise in prescription drug misuse, overdose, and mortality. Also, prescription drugs can impair motor skills to operate safely of a motor vehicle and affect traffic safety. Drug Monitoring Programs (PDMPs) are systems that record substance-dispensing information to prevent, educate, and treat drug abuse. This dissertation systematically reviewed the literature to evaluate the impact of a PDMP on prescription drug abuse and misuse, and overdose. Additionally, this study examined the impact of Florida's PDMP implementation on drug-related motor vehicle crashes occurring on public roads. This cross-sectional study employed a difference-in-differences model and negative binomial regression model to analyze trends in drugged driving-related crashes from the Fatality Analysis Reporting System (FARS) in Florida two years before and after the Florida PDMP implementation in 2011. Results show that states with mandatory use and enrollment PDMPs most likely experience a reduction in prescription misuse, abuse, and mortality. Therefore, PDMPs have become a critical policy tool to help address the Prescription drug crisis in the U.S. Additionally, PDMP implementation in Florida has been associated with a more than 20 percent decrease in prescription opioid-related vehicle fatal crashes.

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| | |
|---|---|
| CNS | Central Nervous System |
| DID | Difference-in-differences |
| EHR | Electronic Health Records |
| FARS | Fatality Analysis Reporting System |
| I-STOP | Internet System for Tracking Over-Prescribing |
| NHTSA | National Highway Traffic Safety Administration |
| PDMP | Prescription Drug Monitoring Program |
| PDMP TTAC | PDMP Training and Technical Assistance Center |
| PEHRIIE | PDMP EHRs Integration and Interoperability Expansion |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| ROB | Risk of Bias |
| SAMHSA | Substance Abuse and Mental Health Services Administration |
| SOE | Strength of Evidence |

# INTRODUCTION

## Introduction and Statement of the Problem

The United States has been struggling with a considerable increase in prescription drug use and misuse associated with a rise in overdose deaths.[1] Between 1999 and 2010, opioid prescription significantly soared by 300 percent.[2] The abuse and misuse of prescription opioids is considered an epidemic in the United States. By 2010, more than 34 million individuals in the United States have had misused opioids in their lifetime.[3] According to the Substance Abuse and Mental Health Services Administration (SAMHSA), in 2012, 15.7 million people used prescription drugs for non-medical purposes in the United States.[4] Consequently, fatal prescription drug overdose rates increased from 1.4 deaths in 1999 to 5.4 deaths per 100,000 people in 2011.[5] In 2008, prescription opioid overdoses surpassed heroin and cocaine overdoses combined, and all drug overdose deaths exceeded motor vehicle crash deaths.[5] Emergency department visit rates for opioids have increased from 214 to 458 visits per 100,000 people between 2004 to 2011.[6] From 1999 to 2017, more than 700,000 individuals died from a drug overdose, of which nearly two-thirds involved opioids, and one-third of those 700,000 individuals, died from prescription opioid overdoses alone.[7]

This crisis compelled policymakers to act. One of the most important steps to control the prescription drug epidemic is the Prescription Drug Monitoring Programs (PDMPs). Through PDMPs, individuals prescribing substance information and patient behaviors will be recorded on an online database system. Prescribers, such as physicians, physician assistants, pharmacists, and program officials, have access to this database. They can check patients prescribing histories and make their prescribing decision based on the available information.[8]

The PDMP Training and Technical Assistance Center (PDMP TTAC) set the main goals for PDMP to prevent prescription drug abuse by providing patients' prescription information to prescribers, pharmacists, and society to develop constructive feedback.[9]

The PDMP enables prescribers to view their patients' prescribing records to identify individuals who forge or illegally obtain prescriptions by visiting multiple physicians. The PDMP restricts drug diversion and controls opioid overdose-related hospitalization by identifying high-risk patients based on their prescription history, gender, demographic variables, number of prescriptions, and opioid overlap.[10] It also helps physicians and physician assistants prescribing drugs that do not have drug interactions.[11] In addition, PDMP increases awareness of the significance of diversion, misuse, and abuse of prescription drugs, which would lead to a decrease in prescription drug diversion, misuse, and abuse. Information gathered from the PDMP can facilitate the development of public health initiatives. Doctor shopping is the practice of visiting multiple physicians to obtain multiple prescriptions. By utilizing PDMP, physicians and physician assistants can access data and identify people aiming to doctor shopping. Pharmacists also can check the patient records online and identify multiple utilization and high-risk prescribing. Additionally, this information could be used to prevent and formulate regulations, new policy implementation, and treatment guidelines.

The origin of PDMPs was the early 20th century when heroin and cocaine were legal by federal and state laws to be prescribed.[12] In fact, the PDMP program has been around for more than one century, but a new era of PDMP has been started in the last decades. In 2002, the state of Virginia took the first action to implement the first PDMP, and other states joined the PDMP gradually. By 2015, Missouri remained the only state that did not have PDMP. In 2016, St. Louis County, Missouri implemented a PDMP law, but there is no state-level PDMP in Missouri. In total, 49 states have active PDMP.[13] Prior to 2010, only a few states had enrollment or use mandate laws. However, starting in 2012, mandating enrollment and query started accelerating, and several states initiated PDMP enrollment and query mandates.[14] Figure 1 shows state PDMP enrollment and query mandates by year.

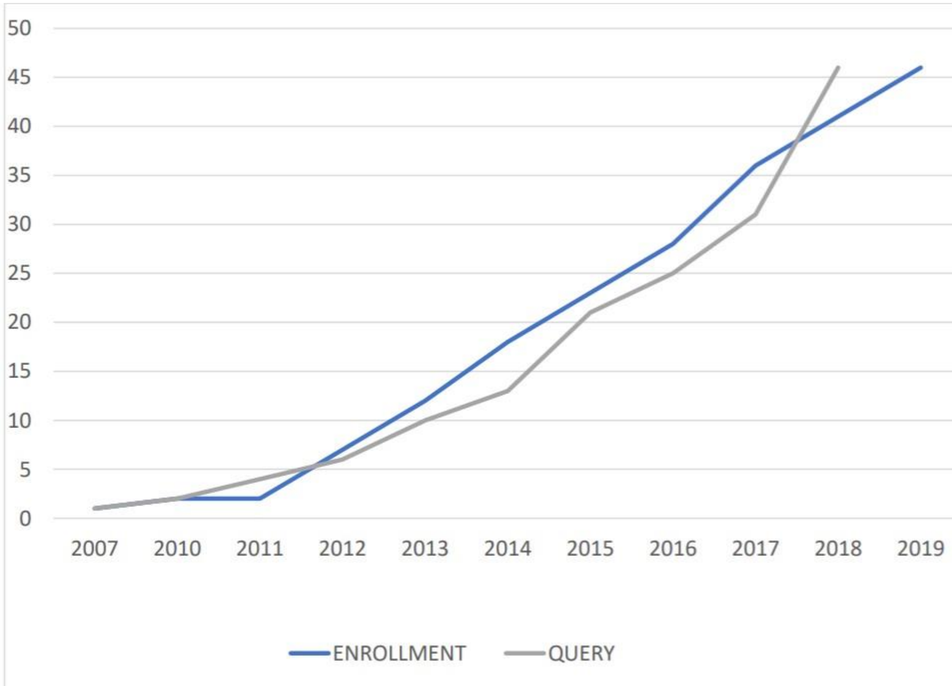



**Figure 1:** State PDMP Enrollment and Query Mandates by Year

Source: PDMP TTAC

The success of the PDMP would be dependent on the legal characteristics of the PDMP in each state. States that mandated utilization of the PDMP for all of the prescribers, dispensers, and pharmacies might have better control over the prescribed opioid. PDMP implementation and administrative features vary widely from state to state.[15] According to the PDMP TTAC,[16] states have different rules about PDMP. Regarding enrollment in 2020, 42 states mandated PDMP for prescribers. There are 32 states with PDMP mandatory enrollment for prescribers and dispensers and eight states with no mandatory enrollment. Also, 47 states had mandatory PDMP query (PDMP use) for prescribers, and Kansas and Nebraska do not have mandatory PDMP query. There are 19 states with PDMP mandatory queries for prescribers and dispensers.

Another very important factor that controls and limits high-risk individuals' access to prescription drugs is the frequency of updating the patient records on the PDMP system. Some states collect and update the data from the point of sales; however, other states update their system in the next business day or two days, which wages a big scape window to the people who aim for doctor shopping. By 2020, all states except Oklahoma and Oregon collect and update the data in the system on the same or the next business day. Oklahoma collects and updates the data in the system at the time of action (the real-time update), and Oregon collects and updates the data in the system no longer than two days). These data are available to prescribers, pharmacies, and law enforcement officials. Figures 2 and 3 show the PDMP mandatory enrollment and query of prescribers and dispensers by the state.

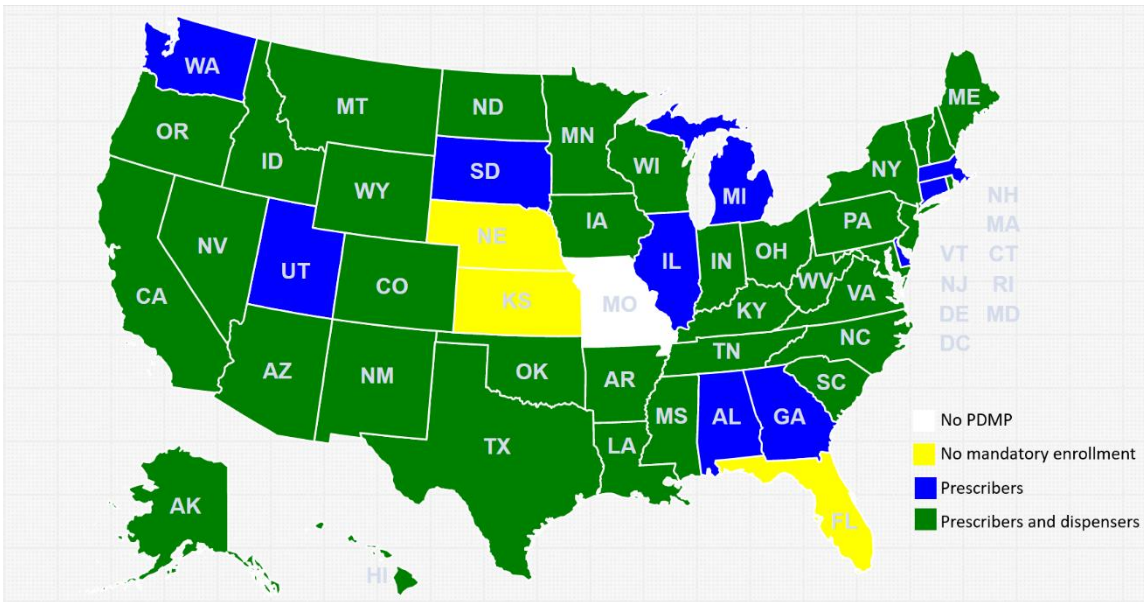



**Figure 2:** The PDMP Mandatory Enrollment for Prescribers and Dispensers by 2020

Source: Data from PDMP TTAC

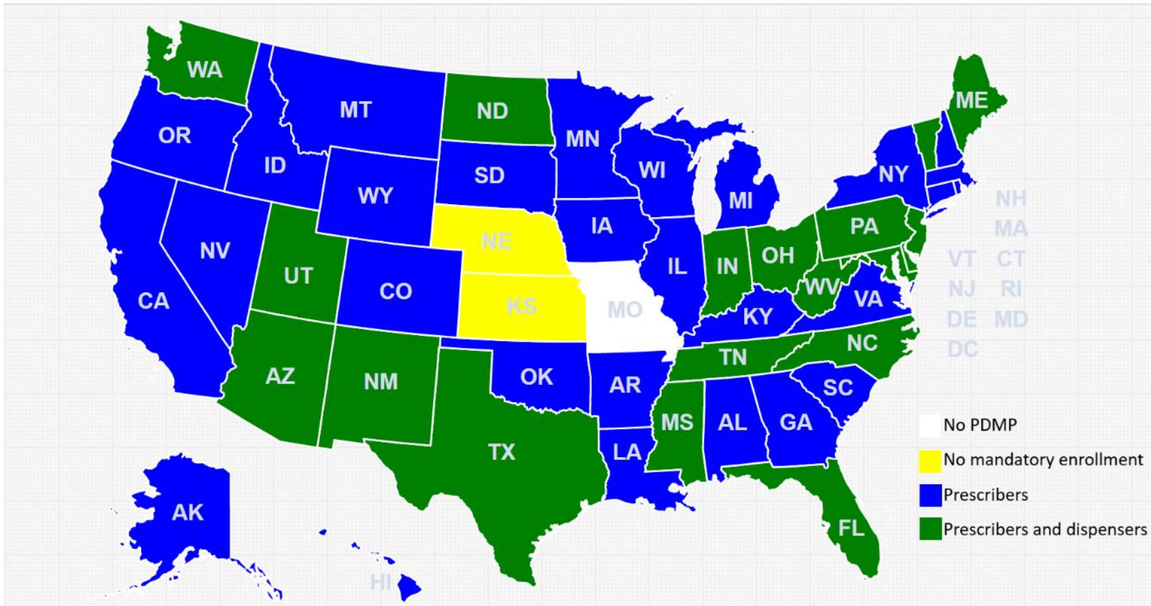



**Figure 3:** The PDMP Mandatory Query by Prescribers and Dispensers by 2020

Source: Data from PDMP TTAC

Although PDMP is an online database that does not have a limitation of the paper passed and fax-based systems,[17] there are new concerns and barriers for PDMP. Prescribers need to spend time checking the patient's records. In addition, before getting access to the data, prescribers need to log on to the system. In general, they have to provide their information, including their names, badge identification, and contact information. A user-specified password and a simple log-on to the system can facilitate the access.[17] The other barrier to implementing PDMP is that most U.S. physicians are aware of PDMPs,[18] but they consider it hard to use they struggle with getting access to it.[19] Lack of evidence-based criteria for considering a person to be categorized as a high-risk person is another challenge of prescribers. In fact, there should be an alert system that predicts overdose, diversion, or abuse.[10] Some PDMPs use proactive alerts to help prescribers identify high-risk patients who go to multiple prescribers and pharmacies and go beyond the thresholds.[20] But this alert has not been totally understood by the prescribers.

Based on Maryland advisory council on prescription drug monitoring,[21] the main costs of PDMP, including startup costs, operate and maintain the program, software run and database costs, connectivity, staff, and administration are ranging from $450,000 to over $1.5 million with an average annual cost of about $500,000. On the other hand, the total cost for prescription opioid-related overdose, abuse, and dependence in 2013 was over $78.5 billion. These costs were related to health care, substance abuse treatment, and lost productivity.[22] This means that PDMP has the potential to not only reduce overdose and mortality but can save billions of dollars that are spent in substance abuse treatment and lost productivity, and invest it in other sectors.

## Conceptual Framework

In 2017, Finley and colleagues developed a conceptual framework to evaluate the impact of PDMP implementation.[23] Their primary goal was to propose a conceptual method to inform upcoming PDMP implementation and evaluations. Due to the combined impact of PDMDs among the states, Finley and colleagues proposed a conceptual framework to clarify the PDMP mechanisms of effects, identifying features of PDMPs reported with supreme outcomes, PDMP policy with the highest utility, and lowest opioid-related public health issues.[23] Figure 4 shows the conceptual model of the impact of PDMPs. Based on each state's PDMP characteristics and legal requirements, our study designed a logic framework and created our conceptual model (Figures 5 and 6).


**Figure 4:** Conceptual Model of the Impact of PDMPs.

Source: Finley et al., (2017)

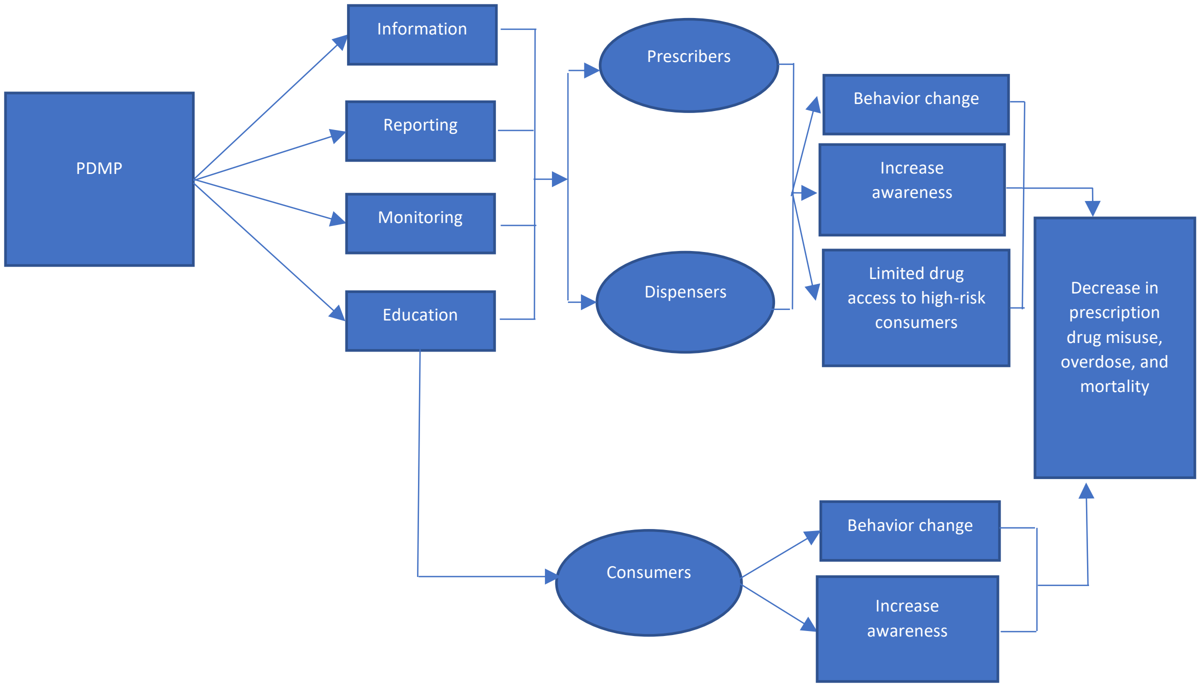



**Figure 5:** PDMP Logic Framework

Source: Author

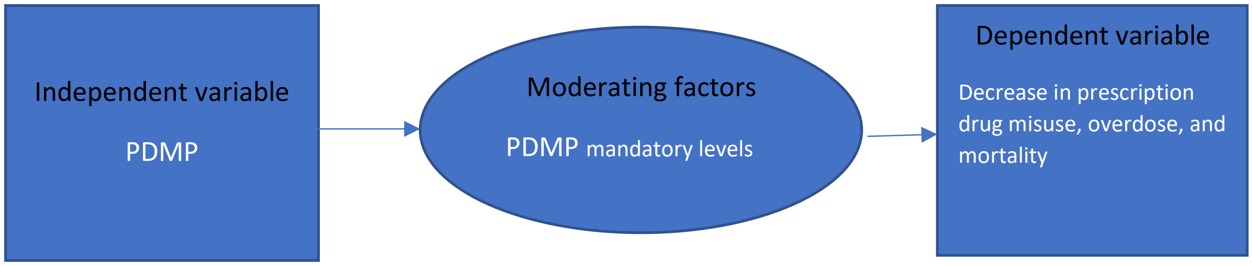



**Figure 6:** Conceptual Model of the Impact of PDMPs

Source: Author

PDMPs record and monitor the patient's prescribing histories and make them available to the prescribers, dispensers, and pharmacists. They can use this information to make better decisions and prevent overdoses because of drug interactions. Also, the patient's prescribing history can help the prescribers and pharmacists identify the high-risk patients and limit their access to prescribed drugs. Suppose a patient aims to possess extra and unnecessary prescription drugs by visiting multiple physicians (doctor shopping). In that case, the system can alarm the physicians and prescribers to prevent potential drug abuse and misuse. In addition, the report provided by PDMP can increase the awareness of the prescribers. For instance, family medicine has one of the highest volumes of prescribed opioids.[24] As a result, awareness of the prescriber increases, and they will also change their prescribing behavior and pattern.

On the consumer side, PDMP increases the awareness of the consumers by the provided information and reports. Many people are not aware of the addictive power of prescribed drugs, especially opioids. People may not be aware of potential opioid overdose incidences. Having enough information and knowledge will also change consumer behavior regarding the prescribed medications. They may change their pain management pattern and stop showing up in ED to control their pain by prescription drugs. They also would be cautious about their extra or unused prescribed opioids and make sure these drugs not available for abuse by their family members and other people around them. PDMP also limits consumer access to prescription drugs. If a person tries to get prescription drugs for non-medical use by visiting multiple physicians, the prescriber can easily identify them by checking their prescribing history. PDMP also has educational programs for prescribers, pharmacists, and consumers, increasing the awareness and significance of prescribed drug misuse and overdose.

**Specific Aims**

Forty-nine states have implemented PDMPs to control the prescription drug epidemic and prevent opioid abuse, misuse, and overdose. Ohio, Kentucky, Florida, New York, Tennessee, and Oregon have had a good PDMP experience, and not only had they controlled overdose death increases, but they also decreased overall overdose death.[25] However, a limited number of states constrains PDMP effectiveness. To our knowledge, there is no comprehensive study about the impact of the PDMP on prescription drugs. Scant literature evaluates the effectiveness of PMDP based on different mandatory implementation levels. Also, there is a gap in our knowledge about the impact of PDMP on fatal car crashes in the US, and our study will help fill this gap.

Our long-term goal is to contribute to how PDMP limits the accessibility of prescription drugs and change prescriber and patient behavior and control abuse, misuse, decrease prescription drug-related overdose and mortality. Thus provide the evidence base that can guide future policies. This study aims to evaluate the impact of the PDMP on prescribed drug abuse, misuse, overdoses, and mortality. Our central hypothesis is that states implementing PDMP with high mandatory levels will experience a reduction in prescription drug-related misuse, abuse, and mortality, compared to states with PDMP with low mandatory levels:

**Hypothesis 1.** States implementing PDMP with high mandatory levels more likely to experience a reduction in prescription drug abuse and misuse than states PDMP with low mandatory levels.

**Hypothesis 2.** States implementing strong PDMP (i.e., high mandatory levels) more likely to experience a reduction in prescribed drug-related fatal car crashes within two years compared to states with no- or weak PDMP.

The rationale that underlies the proposed research is that once we know more about the effect of PDMP on prescription drug abuse, misuse, overdose, and mortality the state, and public health officials can use this knowledge to formulate effective PDMPs. We plan to test our central hypothesis and accomplish the objective of this application by pursuing the following specific aims:

**Aim 1.** To evaluate the impact of a PDMP on prescribed drug abuse and misuse by conducting a systematic review.

**Aim 2.** To determine the effect of PDMP on prescribed drug-related fatal car crashes.

The expected outcome of this study is a substantial increase in our currently limited knowledge of the effect of PDMP on prescription drug abuse, misuse, and mortality. This outcome is expected to significantly positively impact the knowledge base needed by states, public health officials, and localities to formulate effective PDMPs.

## Data Source

This study used PubMed and Scopus online databases, which comprise millions of citations for biomedical literature, including the MEDLINE database for the systematic review. Additionally, this study used Fatality Analysis Reporting System (FARS) database to report prescribed drug-related car crashes. FARS data are available at the state level from 1982 up to 2017. We use data from 2009 to 2013, which is two years before and after the PDMP operation in Florida. We also use The PDMP TTAC website to gain information about PDMP Policies and Procedures, including PDMP characteristics, legislation, and operational dates.

**Study Sample**

The study sample to be used in our study for the systematic review will be 49 states. Even though in 2016, St. Louis County, Missouri implemented a PDMP law, Missouri remained the only state that does not have active state-level PDMP. Also, we will use Florida (the treatment group) and Georgia (the control group) to determine the effect of Florida's PDMP implementation on prescription drug-related fatal car crashes.

# CHAPTER 1: THE ASSOCIATION BETWEEN PRESCRIPTION DRUG MONITORING PROGRAMS AND PRESCRIPTION DRUG ABUSE AND MISUSE: A SYSTEMATIC REVIEW

## Introduction

Over the last two decades, the use of prescription opioids escalated across the U.S.,[26] and this increase was associated with a corresponding rise in overdose deaths.[27-29] From 1999 to 2011, fatal prescription drug overdoses soared from 1.4 deaths to 5.4 deaths per 100,000 people in the U.S.[30] In 2008, prescription opioid overdoses surpassed heroin and cocaine overdoses combined, and all drug overdose deaths exceeded motor vehicle crash deaths.[5] Emergency department visit rates for opioid-related adverse events increased from 214 to 458 visits per 100,000 people between 2004 to 2011.[28] Between 1999 and 2017, 218,000 people died from prescription opioid overdoses alone.[29]

This crisis compelled policymakers to act. Assuming the opioid crisis was the result of information barriers, policymakers designed a tool that would allow providers to share and access a patient's prescription history across different prescribers and dispensers. Prescription Drug Monitoring Programs (PDMP) are systems that record substance-dispensing information in an online database and makes these data available to prescribers, pharmacies, and officials. The PDMP TTAC set its main goals for PDMP as prevention, education, and treatment of drug abuse.[9] In total, 49 states have instituted PDMP systems. In 2016, St. Louis County, Missouri passed a PDMP implementation law, but Missouri still does not have a state-level system.[31]

PDMP implementation and administrative features vary widely from state to state.[15] Administrative features includes state-controlled substances laws, doctor shopping laws, the timing of state PDMP legislation and implementation, and regulatory elements including limitations on pain clinic ownership. Some states offer voluntary enrollment while others require enrollment; some mandate PDMP for prescribers and others for dispensers; a handful of states mandate for both groups. Only 19 out of 49 states have mandatory query for prescribers and dispensers which requires them to check the system before writing or filling a prescription for a controlled substance.[15] Data collection frequency varies as well, which ranges from the point of sale up to 14 days, but most states (42) collect and update data in the system daily.

As states have implemented PDMPs to address the opioid epidemic, a growing number of studies have attempted to examine the effectiveness of these PDMPs.[32-38] For example, prior research by the Centers for Disease Control and Prevention suggests that mandatory PDMPs in the states of Ohio and Kentucky were very successful in decreasing prescriptions.[36] For these states, Morphine Milligram Equivalents (MME) per capita decreased in 85 percent of counties since the year 2010. Additionally, PDMP mandatory regulations in Florida resulted in a decrease of opioids prescribed in 80 percent of counties from 2010 to 2015.[36] Although the evidence base on PDMPs is growing, a systematic review has not been undertaken, to our knowledge, that summarizes and evaluates the quality of prior studies on PDMP effectiveness same as our study scope and time span.[39-42] To address this knowledge gap, our study reviews the existing literature to evaluate the impact of a PDMP on prescribed drug abuse and misuse.

Furthermore, we provide a review of prior studies that explored the association between specific PDMP administrative features such as mandatory-access and PDMP implementation on drug abuse and misuse outcomes.

## Methods

This study was conducted based on structured reporting of a systematic review according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.[43] Approval by an institutional review board was not required for this systematic review.

**Data Sources and Searches**

We systematically searched online databases, including PubMed and Scopus, on September 30, 2019. We used PubMed and Scopus which comprise millions of citations for biomedical literature including MEDLINE database. They are also interdisciplinary research databases and have a broad scope and hosted at the National Institutes of Health (NIH). Our search aimed to find articles that evaluated the association between PDMPs and prescription drug overdoses published anytime prior to September 30, 2019. The search terms included: “PDMP” OR "prescription drug misuse" OR "prescribed drug misuse" OR "prescription drug monitoring program" OR "prescription monitoring" OR "prescription opioid misuse" OR "prescription drug abuse" OR "prescribed drug abuse" OR "prescription opioid misuse". We included peer-reviewed articles and published texts. We excluded abstracts, dissertations, and in-progress texts. We did not impose time restrictions, but non-English and non-U.S. related publications were excluded. Our search on PubMed and Scopus did not reveal any English language systematic review on this topic as of September 30, 2019. Table 1. 1 shows search strategy of the study.

**Table 1. 1:** Search Strategy of the Study

| **Search Strategy** | |
|---|---|
| **Search date** | September 30, 2019 |
| **Information sources** | Scopus, PubMed |
| **Search terms** | "prescription drug monitoring program" OR "prescription monitoring" OR "prescription drug misuse" OR "prescribed drug misuse" OR "prescription opioid misuse" OR "prescription drug abuse" OR "prescribed drug abuse" OR "prescription opioid misuse" |
| **Limits** | English, article, final |
| **Total records identified through database searching** | 3331 |
| **Scopus results** | 2020 |
| **PubMed results** | 1311 |
| **Duplicate articles** | 941 |
| **Record screened** | 2390 |
| **Record excluded, did not meet inclusion criteria** | 2135 |
| **Full-text articles assessed for eligibility** | 255 |
| **Studies excluded** | 247 |
| Qualitative | 23 |
| Provider Perspective | 122 |
| Review/Commentary | 50 |
| Not Evaluating PDMP | 14 |
| Other | 33 |
| **Studies included** | 13 |

**Study Selection**

First, we checked the retrieved articles and removed duplicates. Afterward, all of the titles and abstracts were screened and reviewed by two independent investigators (M.T. and V.P.) to verify their relevance to the study. To establish the final list of the eligible articles, the two investigators independently reviewed the full-text of the eligible studies. A third investigator (F.W.) resolved discrepancies, and the final list of the published texts was established.

**Data Extraction and Quality Assessment**

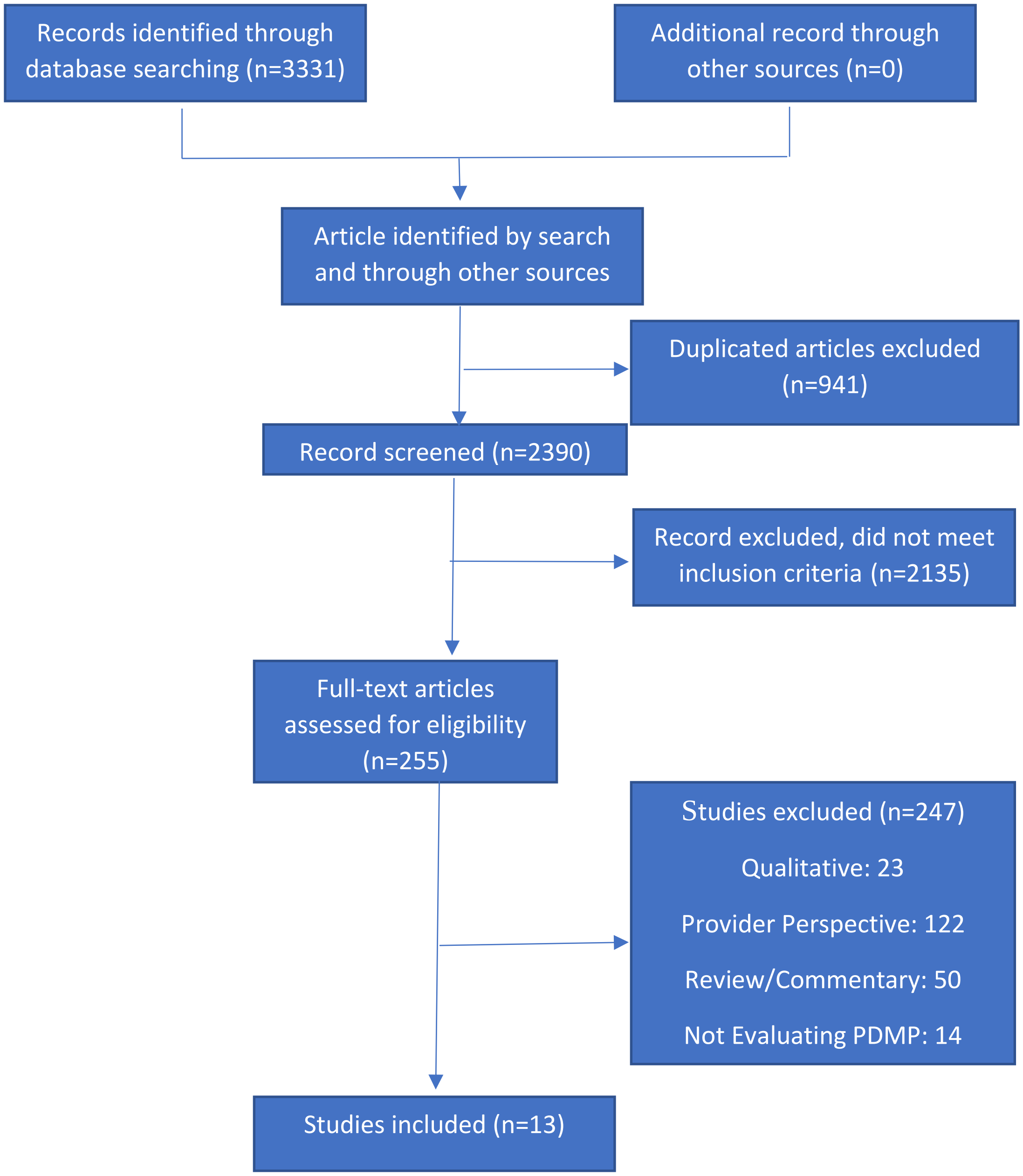
The two researchers (M.T. and V.P.) independently read and extracted data from the selected articles. They used a standardized article assessment form to capture data from the article, including study sample characteristics, study design, study duration, levels of PDMP mandate and implementation, outcomes, and results. After the two researchers independently extracted the data from the articles, they investigated any inconsistencies and resolved differences through consultation with a third investigator (F. W.). At the end of the study, the two researchers, using the Cochrane Risk Of Bias In Non-randomized Studies of Interventions (ROBINS-I) assessment tool, independently assessed Risk of Bias (ROB) for the outcomes.[44] This tool provides eight questions to assess the biases including confounding, selection of participants, classification, deviations from intended interventions, missing data, measurement of outcomes, selection of the reported results, and overall bias. The domain biases independently graded as low, moderate, serious, or critical, and disagreement was resolved by consensus.

**Data Synthesis and Analysis**

We categorized studies into two groups: Mandatory-access PDMP (states with mandatory enrollment and query of prescribers and dispensers compared with states that do not have those features) and pre/post PDMP implementation. We examined four outcomes: admission (ED visit for prescription-related diagnoses), prescription opioid mortality from overdose, non-medical prescription diversion rates, and prescription opioid consumption (prescriptions per capita). We evaluated the overall Strength of Evidence (SOE) of the intervention and outcomes across five main domains, including: limitations, directness, consistency, precision, and reporting bias.

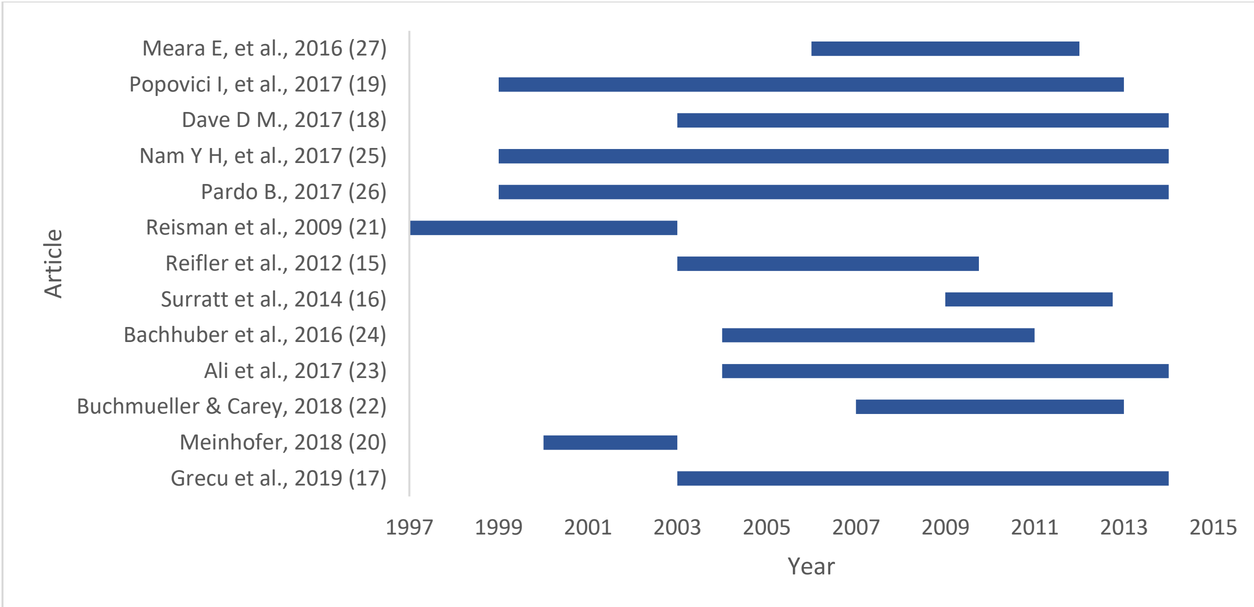
**Results**

Figure 1. 1 shows the study selection process. In total, 3,331 records were identified through PubMed and Scopus databases, 941 of which were duplicates. After reading the title and abstract, we excluded 2,135 articles because they did not meet the aims of the study, per our as inclusion criteria. Finally, 255 full-text articles were assessed for eligibility, and 247 were excluded for the following reasons: 33 articles were qualitative, 122 articles discussed provider or pharmacist perspective, 50 articles offered review and/or commentary, 14 articles did not specifically evaluate PDMP, and 33 articles were excluded for other reasons. Thirteen articles met the inclusion criteria and are included here for analysis. All of the articles were published in peer-reviewed journals between 2009 and 2019. Figure 1. 2 shows Lengths of study, by article.. Table 1. 2 shows the ROB assessment of the selected studies.




PDMP = prescription drug monitoring program.
Article identification and study selection process adapted from PRISMA

**Figure 1. 1:** Study Selection Process




Span of years analyzed in the included studies.

**Figure 1. 2:** Lengths of Study, by Article

**Table 1. 2:** ROB Assessment

| Bias | Grecu et al., 2019 | Meinhofer, 2018 | Buchmueller & Carey, 2018 | Ali et al., 2017 |
|---|---|---|---|---|
| Bias due to confounding | Low – adequate adjustment for sociodemographic, co-implemented policies, time-invariant differences, and PDMP features. | Moderate – adequate adjustment for time-invariant differences, and PDMP features; inadequate adjustment for sociodemographic and co-implemented policies. | Low – adequate adjustment for sociodemographic, co-implemented policies, time-invariant differences, and PDMP features. | Moderate – adequate adjustment for time-invariant differences, and PDMP features; inadequate adjustment for sociodemographic and co-implemented policies. |
| Bias in selection of participants | Low – selection of 50 U.S. states | Low – selection of 49 U.S. states | Low – selection of 50 U.S. states and D.C. | Low – selection of 50 U.S. states |
| Bias in classification of interventions | Low – intervention was clearly defined | Low – intervention was clearly defined | Low – intervention was clearly defined | Low – intervention was clearly defined |
| Bias due to deviations from intended intervention | Low – no deviation from intended intervention | Low – no deviation from intended intervention | Low – no deviation from intended intervention | Low – no deviation from intended intervention |
| Bias due to missing data | Low – no missing data were reported | Moderate – states with zero counts were imputed | Low – no missing data were reported | Low – no missing data were reported |
| Bias due to measurement of outcomes | Low – measurement of outcome independent of policy | Low – measurement of outcome independent of policy | Low – measurement of outcome independent of policy | Low – measurement of outcome independent of policy |
| Bias in selection of reported results | Low – expected analyses were reported | Low – expected analyses were reported | Low – expected analyses were reported | Low – expected analyses were reported |
| **Overall bias** | **Low** | **Moderate** | **Low** | **Moderate** |

**Table 1. 2:** ROB Assessment (cont.)

| Bias | Bachhuber et al., 2016 | Surratt et al., 2014 | Reifler et al., 2012 | Reisman et al., 2009 |
|---|---|---|---|---|
| Bias due to confounding | Serious – inadequate adjustment for sociodemographic, co-implemented policies, time-invariant differences, and PDMP features. | Critical – inadequate adjustment for co-implemented policies, time-invariant differences, and PDMP features; no adjustment for sociodemographic. | Serious – inadequate adjustment for sociodemographic, co-implemented policies, time-invariant differences, and PDMP features. | Moderate – adequate adjustment for sociodemographic; inadequate adjustment for co-implemented policies and PDMP features. |
| Bias in selection of participants | High – selection of small number of metropolitan areas | High – case reports are a sample of law enforcement reports, not representative, did not cover all areas of state | Moderate – selection of 44 states that report to system; limited power of the secondary analysis of states | Low – selection of 50 U.S. states |
| Bias in classification of interventions | Moderate – measures of PDMP utilization were not consistently available; no lag between implementation and outcome | Low – intervention was clearly defined | Low – intervention was clearly defined | Low – intervention was clearly defined |
| Bias due to deviations from intended intervention | Low – no deviation from intended intervention | Low – no deviation from intended intervention | Low – no deviation from intended intervention | Low – no deviation from intended intervention |
| Bias due to missing data | Low – no missing data were reported | Low – no missing data were reported | Moderate – missing data are queried with sites; unresolved cases are removed from the data, more conservative estimate of misuse | Moderate – ARCOS data for year 2000 missing re: annual shipments of codeine and morphine |
| Bias due to measurement of outcomes | Low – measurement of outcome independent of policy | High – policy implementation and diversion rates may not be independent; case reports are not perfect measures, so reporting biases are possible | Moderate – observational data are subject to self-report and selection bias; data only capture individuals contacting poison centers/entering treatment programs, likely underestimate of abuse | Low – measurement of outcome independent of policy |
| Bias in selection of reported results | Low – expected analyses were reported | Low – expected analyses were reported | Low – expected analyses were reported | Low – expected analyses were reported |
| **Overall bias** | **Serious** | **Critical** | **Serious** | **Moderate** |

**Table 1. 2:** ROB Assessment (cont.)

| Bias | Pardo B., 2017 | Nam Y H, et al., 2017 | Dave D M., 2017 | Popovici I, et al., 2017 | Meara E, et al., 2016 |
|---|---|---|---|---|---|
| Bias due to confounding | Low -- robust adjustment for sociodemographics and adjustment for co-implemented policies; robust adjustment for PDMP implementation characteristics and funding | Moderate -- state and year fixed-effects for time-invariant differences; robust adjustment for sociodemographics; inadequate adjustment for co-implemented policies; inadequate adjustment for PDMP implementation characteristics | Low -- robust adjustment for PDMP implementation characteristics; robust adjustment for sociodemographics and adjustment for co-implemented policies | Moderate -- robust adjustment for sociodemographics; robust adjustment for co-implemented policies; inadequate adjustment for PDMP implementation characteristics | Moderate -- robust adjustment for personal characteristics, including sociodemographics, comorbidities; no adjustment for PDMP implementation characteristics |
| Bias in selection of participants | Low -- selection of 50 U.S. states and D.C. | Moderate -- selection of 19 states covering one time period and 34 states covering a second time period | Low -- selection of 49 U.S. states | Low -- selection of 50 U.S. states | Moderate -- sample included feed-for-service disabled beneficiaries of Medicare, age 21-64 |
| Bias in classification of interventions | Low -- intervention was clearly defined | Low -- intervention was clearly defined | Low -- intervention was clearly defined | Low -- intervention was clearly defined | Low -- intervention was clearly defined |
| Bias due to deviations from intended intervention | Low -- no deviation from intended intervention | Low -- no deviation from intended intervention | Low -- no deviation from intended intervention | Low -- no deviation from intended intervention | Low -- no deviation from intended intervention |
| Bias due to missing data | Low -- reasonable imputation for minimal missing data | Low -- no missing data were reported | Low -- fewer than 2 percent of observations have missing values | Low -- no missing data were reported | Low -- no missing data were reported |
| Bias due to measurement of outcomes | Low -- measurement of outcome independent of policy | Low -- measurement of outcome independent of policy | Low -- measurement of outcome independent of policy | Low -- measurement of outcome independent of policy | Low -- measurement of outcome independent of policy |
| Bias in selection of reported results | Low -- expected analyses were reported | Low -- expected analyses were reported | Low -- expected analyses were reported | Low -- expected analyses were reported | Low -- expected analyses were reported |
| **Overall bias** | **LOW** | **Moderate** | **Low** | **Low** | **Moderate** |

ROB: risk of bias.

Both state-level and national datasets were used to obtain outcome data. Two studies used a state-level database called the Researched Abuse Diversion and Addiction-Related Surveillance System (RADARS).[37,38] The other studies used national data: Treatment Episode Data Set (TEDS) on demographic and substance abuse of all admissions.[34,35,45] Automated Reports and Consolidated Ordering System (ARCOS) ;[46,47] National Vital Statistics System's (NVSS) ;[46] Centers for Medicare and Medicaid Services (CMS);[32] Substance Abuse and Mental Health Services Administration (SAMHSA);[47,48] Drug Abuse Warning Network (DAWN);[49] Researched Abuse, Diversion and Addiction-Related Surveillance (RADARS®);[37,38] the Centers for Disease Control and Prevention's (CDC's);[50,51] Wide-ranging Online Data for Epidemiologic Research database (WONDER);[50,51] Prescription Drug Abuse Policy System (PDAPS);[51] Treatment Episode Data Set (TEDS);[34,45] National Vital Statistics Mortality Files (NVSM);[45] National Death Index;[52] Medicare claims;[52] and National Alliance for Model State Drug Laws (NAMSDL).[37,46,51]

All thirteen studies examined the association between PDMP implementation and/or administrative features and prescription abuse/misuse: Eleven examined the effect of PDMP implementation,[32,37,38,45-52] Five studies examined mandatory-access PDMP.[32,34,35,46,48] Two studies examined prescriber-accessible PDMPs.[48,49] Two studies examined PDMP robustness.[37,51] One study examined statewide regulatory elements, of which PDMP implementation was a component.[38]

The heterogeneity of PDMP implementation and concurrent policies between states compelled us to assess the strength of evidence (SOE) for each comparison. Table 1. 3 summarizes the SOE assessment across the following ROBINS-I domains: limitations, directness, consistency, precision, and reporting bias.

**Table 1. 3:** Table 3. SOE Assessment

| | | Strength of evidence domains | | | | | |
|---|---|---|---|---|---|---|---|
| **Comparison** | Studies, n | Limitations | Directness | Consistency | Precision | Reporting bias | Overall SOE |
| **PDMP versus no PDMP** | 10 | Moderate | Direct | Inconsistent | Imprecise | None detected | Low |
| **Mandatory access PDMP versus non-mandatory access PDMP** | 6 | Low | Direct | Consistent | Precise | None detected | Moderate |
| **Direct access PDMP versus gatekeeper PDMP** | 3 | Serious | Direct | Consistent | Precise | None detected | Low |
| **Pre-implementation versus post-implementation** | 3 | Serious | Direct | Inconsistent | Imprecise | None detected | Low |
| **Prescriber-accessible PDMP** | 3 | Serious | Direct | Inconsistent | Imprecise | None detected | Insufficient |
| **Superior PDMP versus standard PDMP** | 3 | Moderate | Direct | Unknown (single study) | Imprecise | None detected | Low |
| **Limitations on pain clinics** | 2 | Serious | Indirect | Unknown (single study) | Imprecise | None detected | Insufficient |

SOE: strength of evidence.

SOE was strongest for mandatory-access PDMPs as compared to PDMPs that do not require providers or prescribers to access the systems. Other PDMP comparisons were not as robust, due to the limited number of studies evaluating abuse/misuse, as well as inconsistency and imprecision of results. As a result, the studies presented here generally reflect insufficient SOE to draw conclusions.

Among studies that examined mandatory-access PDMP, all compared states with and without mandatory-access provisions for their PDMPs.[34,35,37,45-48,50-52] Only one estimated the effect of mandatory-access PDMP on non-medical use of prescription drugs by measuring substance abuse treatment admission.[35] Seven studies estimated prescription opioid use, misuse, and abuse by considering death or poisoning including fatal and non-fatal overdoses.[32,35,45,46,50-52] One examined total grams of drugs available to attempt to capture legal supply of prescription drugs available at the provider level.[46] Two studies considered consumer behavior, including overlapping claims, non-medical prescription rates, sources of non-medical prescription drugs for misuse.[32,48] One study also examined the effect of PDMP implementation on heroin initiation, abuse, and dependence.[46]

The overall strength of evidence for mandatory-access PDMP was strongest among the interventions considered – specifically, studies examining the association between mandatory-access PDMP and abuse/misuse suffered from minimal methodological shortcomings, the evidence linking interventions and outcomes was direct, and findings were consistent across studies. While they found no evidence that an operational PDMP significantly affects treatment admissions related to non-medical prescription drug abuse,[35] drug quantities,[46] or overdose events,[32,35,46] they presented robust evidence PDMP with mandatory-access provisions reduced prescription drug abuse,[34,35,46] reduced prescription opioid and stimulant quantities,[32,46] reduced overdose deaths,[32,35,45,46,51] and reduced patient extreme utilization behaviors.[32,46,48].

The overall strength of evidence was much lower for studies examining the effect of PDMP implementation, due to methodological limitations, inconsistent results, imprecise certainty, and inadequate adjustment for concurrent policies. Of the studies that examined the effect of PDMP implementation,[32,37,38,45-49] five assessed the effect of PDMP implementation and prescription opioid shipment and use.[32,37,46,47,52] Four studies found PDMP implementation alone had no significant effect on prescription drug use.[32,34,46,52] One study reported a decrease in doctor shopping behavior after PDMP implementation.[48] Two studies found decrease in prescription opioid overdose death.[45,51] One study found declines in oxycodone, methadone, and morphine use in diversion rates in Florida after a suite of policy interventions,[38] and one study reported a decrease in the quantity of oxycodone shipment.[47] One study looked at rates of ED visits involving benzodiazepine misuse and found PDMP implementation was associated with an increase in ED visits.[49]

Three studies examined the effects of PDMP implementation on treatment admissions.[35,37,47] Two studies found no evidence that an operational PDMP significantly affects treatment admissions related to prescription drug abuse[35,50], while another found PDMPs were associated with mitigated opioid abuse due to increased treatment admissions.[33] The other study found that PDMPs were associated with a decrease in prescription opioid admission rates for states with PMDPs implemented.[47]

Three studies analyzed PDMP effects on non-prescription drug use and abuse.[35,46,48] Two studies found a decrease in cocaine abuse after the implementation of mandatory-access PDMP.[35,46] Two other studies examined changes in heroin use,[46,48] but found different effects of PDMP implementation and administrative features on initiation, abuse, and dependence of heroin.

## Discussion

The aims of this systematic review were to explore the existing literature to evaluate the effects of PDMP on prescribed drug abuse, misuse, and potential unintended PDMP consequences. Second, to explore the association between different PDMP administrative features and implementation characteristics with rates of abuse and misuse.

To those ends, evidence was insufficient to conclude that operational PDMPs had an impact on prescribed drug abuse or misuse. Further, there is no evidence that operational PDMPs significantly affected treatment admissions related to non-medical prescription drug abuse, drug quantities, and overdose events. However, evidence suggests that mandatory-access provisions may change patient and prescriber behavior in intended ways. Of the four studies that explored the association between mandatory-access PDMP and abuse/misuse, they offer emerging evidence that mandatory-access provisions are significantly associated with reduced prescription drug abuse,[35] reduced prescription opioid and stimulant quantities,[32,46] reduced overdose deaths,[32,35,46] and reduced patient extreme utilization behaviors.[32,48] In terms of unintended negative consequences, two studies found PDMP implementation was associated with a decrease in cocaine abuse,[35,46] while two studies found different effects of PDMP implementation and administrative features on initiation, abuse, and dependence of heroin.[46,48] Due to methodological limitations, inconsistent results, imprecise certainty, and inadequate adjustment for concurrent policies, the overall SOE was relatively low. More research is required to determine best practices to guide clinical management for providers. Once best practices have been determined, developing clinically actionable guidelines for PDMP data interpretation training clinicians to engage patients with suspicious or aberrant prescription, may improve the effectiveness of PDMP.

Our study should be interpreted in the context of certain limitations. There is limited existing literature on the relationship between PDMPs and prescription drug abuse and misuse, and the need for further studies is obvious. We were able to find eight eligible studies, and only three studies examined prescription opioid use, misuse, and abuse by considering death or poisoning including fatal and non-fatal overdoses. The studies generally reflected insufficient SOE to draw conclusions about the efficacy of PDMP implementation. Because our study was limited to peer-reviewed articles published in English and found in Scopus and PubMed engines on September 30, 2019, we may have missed some analyses, particularly dissertations, in-process texts, and grey literature.

## Conclusions

In spite of the concerted efforts of state and national stakeholders, our study suggests that policy adjustments may improve PDMP effectiveness. PDMPs appear to hold great potential as public health tools to curb opioid misuse and abuse. However, evidence is mixed, limited, or non-existent about whether implementing an operational PDMP has its intended effect. Like any tool, the promise of PDMPs can be realized only if they are designed and used effectively. For example, mandating all health care providers use PDMPs to inform their prescribing strategies may have a significant effect on patient and provider behavior. Furthermore, providers must expect access to “real-time” data to have the best understanding of how to best serve their patients and mitigate “doctor shopping”. Finally, robust PMDPs should be actively managed and user-friendly for providers to access and utilize.

While thoughtfully designed PDMPs may change patient and provider behavior, more research must be done to evaluate how these administrative features impact abuse and misuse. Ultimately, a lack of relevant and robust studies primarily reveals the need for additional, rigorous research to answer the study questions. The evidence currently available for review allows only the speculation that PDMP implementation and individual elements are associated with reductions in prescription-drug related adverse events, and characteristics of abuse-related factors upon admission to addiction programs. More robust evaluations of state PDMPs may reveal the most promising ways to design, implement, and administer the systems. Furthermore, PDMPs may be more or less effective for targeting different types of patients. For example, to our knowledge, there is no research currently considers the effect of socioeconomic or other demographic factors on the effectiveness of PDMP. Teasing out the relative effectiveness of PDMP on different types of patients may reveal other opportunities for more targeted surveillance and intervention.

# CHAPTER 2: THE IMPACT OF FLORIDA'S PRESCRIPTION DRUG MONITORING PROGRAM IN DECREASING PRESCRIPTION DRUG-RELATED VEHICLE CRASH FATALITIES

## Introduction

The use of prescription opioids has escalated across the US within the last two decades.[26,53] Approximately one-third of all deaths involved prescription opioid use in 2017.[28] This increase was associated with a rise in drug-related fatal crashes,[54] and drug overdose and motor vehicle injuries have become the leading causes of unintentional injury mortality in the United States.[55] Florida experienced an 80% increase in prescription drug overdose deaths from 2003 to 2009.[56] In 2010, 90 out of 100 physicians who had the highest amounts of oxycodone prescribing in the US were located in Florida.[57] Prescription drug use may impair cognitive and psychomotor skills necessary for safe operation of a motor vehicle.[58,59] From 1995 to 2015, the prevalence of prescription opioids found in fatally injured drivers increased from 1% to 7%, [60] and soared to 10.7% in 2016.[61]

The prescription drug epidemic compelled policymakers to respond to and legislate statewide interventions. Prescription Drug Monitoring Programs (PDMPs) are online systems that record controlled substance-dispensing information.[62] Prescribers who utilize PDMPs can check patient history to identify high-risk individuals based on their prescription history, age, number of prescriptions, and overlap in opioid prescriptions,[10] and prevent potential drug interactions for patients taking multiple prescriptions.[63] PDMPs also help identify individuals who forgo or illegally obtain prescriptions by visiting multiple prescribers and dispensers ("doctor shopping") and restricts the diversion of the prescribed drug and thus helps control opioid misuse. In 2010, Florida implemented legislation to combat "pill mills", i.e., clinics that prescribed opioids and other medications inappropriately.[64] The law required clinics to register with the state and have a physician owner and operator, and restricted the prescribing and dispensing drugs by physicians at these clinics. The pill mill law was fully implemented in July 2011.[65] Shortly afterward, in September 2011, Florida's PDMP program became operational.[66] Unlike PDMP programs in other states, participation in Florida's PDMP by prescribers is mandatory. By September 2012, the number of registered prescribers and queries to the PDMP totaled 18,000 and 2.3 million, respectively.[67]

There are limited studies that examined the effectiveness of Florida's PDMP. For example, a research found PDMP implementation in Florida were associated with modest decreases in opioid prescribing and use.[57] A recent study also reported a significant decline in diversion rates for oxycodone, methadone, morphine, and hydrocodone following the implementation of Florida's PDMP.[38] Another study found that oxycodone-caused mortality declined 25% in Florida after PDMP implementation.[68] However, to our knowledge, our study is the first to investigate the impact of a statewide PDMP on traffic safety. The primary aim of our research was to examine and analyze the impact of a statewide PDMP on prescription drug-related vehicle crash fatalities on public roadways in the state of Florida.

## Methods

### Study Setting, Design, and Data Sources

In this study, we used data from the Fatality Analysis Reporting System (FARS) to analyze prescription opioid-related vehicle crash fatalities. FARS is a nationwide census-level database providing detailed data on all fatalities to a vehicle occupant or non-motorist occurring on public roadways within 30 days of the crash.[69] FARS data are available for all 50 states, the District of Columbia, and Puerto Rico. We used data from 2009 to 2014, which is more than two years before and after the PDMP operation in Florida (implemented in September 2011). We also used the PDMP TTAC website to gain information about PDMP policies and procedures and also PDMP legislation and operational dates.[70] Monthly unemployment rates and gasoline prices were obtained from the US Department of Labor and US Energy Information Administration, respectively.[71,72] We also used monthly gasoline consumption as a proxy for vehicle miles traveled in Florida. We obtained these data from the US Department of Transportation.[73]

**Statistical Analysis**

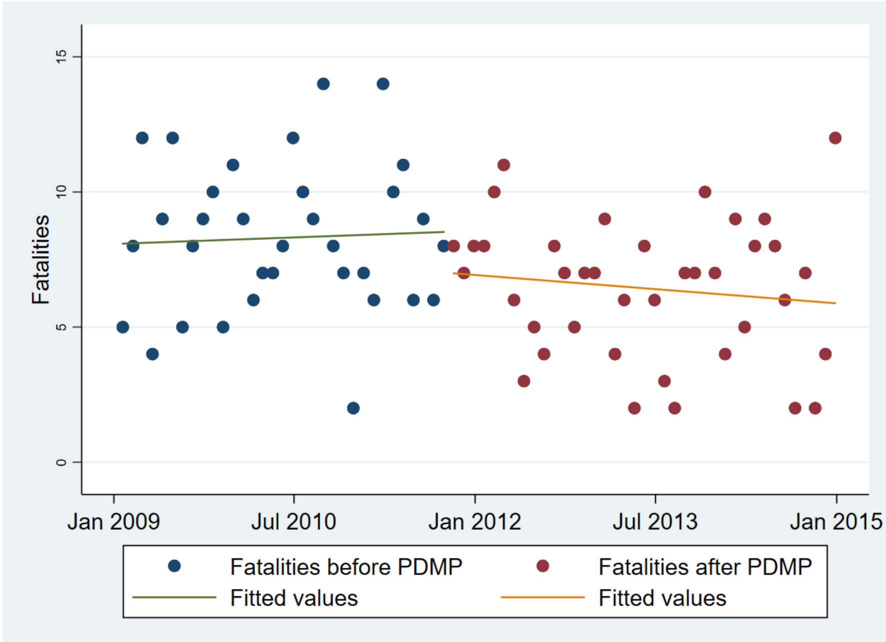
FARS data offer detailed information on the event, the vehicles, drivers, and each person involved in the crash. We identified and included fatal crashes in which drivers tested positive for prescription opioids in blood, urine, or both blood and urine in toxicological testing. Examples of prescription opioids include hydrocodone, oxycodone, and methadone. We excluded drugs with no currently accepted medical use (US Drug Enforcement Agency Schedule I drugs) such as, for example, heroin and cannabis. Inhalants including glue, paint, etc. were also excluded from the analyses. In total, 508 crashes with 525 fatalities were included in our study.

The primary outcome of the study was the number of monthly fatalities in vehicle crashes in which drivers tested positive for prescription opioids. We defined an indicator variable that was assigned zero before PDMP implementation in September 2011 and one after September 2011. The monthly unemployment rates, gasoline prices, and motor fuel consumption (gasoline and gasohol in gallons) were additional predictor variables.

Count-data modeling techniques are prevalent for crash frequency analysis because the number of crashes is a non-negative integer[74]. Because crash frequency data are overdispersed, we utilized the negative binomial regression model instead of a Poisson regression model to analyze prescription drug-related crashes before and after PDMP implementation in Florida [75]. We also performed a t-test on the differences of fatalities before and after Florida's PDMP implementation. Finally, we conducted sensitivity analyses and repeated our analyses for prescription stimulant, depressant, and all prescription drugs. We used the Stata SE 15.1 (College Station, TX) statistical package for all analyses.

## Results

Figure 2. 1 shows the trend in prescription narcotic-related vehicle crash fatalities before and after PDMP implementation in Florida. Prior to September 2011, fatalities exhibited a positive trend since 2009. After PDMP implementation, fatalities significantly decreased.




*PDMP: prescription drug monitoring program.
Florida PDMP program became operational in September 2011.

**Figure 2. 1:** The effect of PDMP implementation in Florida on prescription opioids-related vehicle crash fatalities

Result of a two-sample t-test comparing the number of prescription narcotic-related vehicle crash fatalities before and after PDMP implementation in Florida showed that there was a statistically significant difference in the monthly number of fatalities before (Mean=8.31; 95% Confidence Interval (CI), 7.29-9.39) versus after (Mean=6.84; 95%CI, 5.66-7.29) PDMP implementation, a difference of 1.8 fewer fatalities every month post-PDMP.

We utilized negative binomial regression to estimate the Incidence Rate Ratios (IRR) for prescription narcotic-related vehicle crash fatalities before and after PDMP implementation in Florida (Table 2. 1) The total number of observations used in the analysis was 72 months. Results indicate a 22% decreased likelihood of a opioids-related fatality post-PDMP (IRR=.78; 95%CI, .65-.92). This translates into a 1.8 decrease in the monthly number of prescription narcotic-related vehicle crash fatalities after the PDMP implementation or more than 70 fewer fatalities from September 2011 to the end of December 2014. In the negative binomial model, we included unemployment rates, gasoline prices, and gasoline motor fuel consumption as a proxy for vehicle miles traveled. However, coefficients for these variables were not statistically significant (see Appendix Table A2. 1)

**Table 2. 1:** Negative binomial regression, Incidence Rate Ratios (IRR), and predicted decrease in monthly fatalities for prescription drugs

| Drug category | Fatals | PDMP | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|
| All drugs | IRR | 0.92 | 0.17 | [0.83 | 1.03] |
| | Predicted decrease in monthly fatalities | -1.43 | 0.17 | [-3.47 | 0.61] |
| Opioids | IRR | 0.78 | <0.01 | [0.65 | 0.92] |
| | Predicted decrease in monthly fatalities | -1.81 | <0.01 | [-3.04 | -0.58] |
| Depressant | IRR | 0.8 | <0.01 | [0.68 | 0.93] |
| | Predicted decrease in monthly fatalities | -1.93 | <0.01 | [-3.27 | -0.6] |
| Stimulant | IRR | 1.1 | 0.30 | [0.92 | 1.33 |
| | Predicted decrease in monthly fatalities | 0.73 | 0.30 | [-0.66 | 2.12] |

PDMP: prescription drug monitoring program.

We also adjusted for seasonality in crash fatalities by creating an indicator variable for each month in which a crash occurred (see Appendix Table A2. 2). We also estimated the model for all drug categories and other sub-categories of drugs. The results show that the impacts of the PDMP for the combination of all categories and stimulants were not statistically significant (see Table 2. 1). However, the PDMP did result in a significant decrease in depressant-related driving fatalities, which decreased by 20% (95%CI, .68-.93). Moreover, we repeated the analysis using a truncated negative binomial regression model and compared it to the negative binomial regression model and the results were substantively the same. (see Appendix Table A2. 3 Appendix). Finally, it is possible that the PDMP resulted in substitution of prescription drugs by illicit drugs such as heroin. Therefore, we checked for changes in heroin-related vehicle crash fatalities in addition to cocaine-related and marijuana-related vehicle crash fatalities before and after PDMP implementation, but we did not find any statistically significant differences

**Discussion**

Our study aimed to examine and analyze the impact of a statewide PDMP on prescription drug-related fatalities from crashes on public roadways in the state of Florida. Our results suggest that the number of narcotic-related fatalities decreased by 22 percent. This means that prescription narcotic-related vehicle crash fatalities after Florida's PDMP implementation declined by nearly two fatalities per month. Additional analyses of other drug types suggest that the impact of PDMPs is not uniform across drug types. For example, although depressant-related crash fatalities significantly decreased, we found no significant difference for stimulants or all drugs pre- and post-PDMP.

In Florida, motor vehicle fatalities totaled more than 2,500 cases each year from 2008 to 2012,[76] and fatalities per 100,000 population and fatalities per 100 million vehicle mile traveled were above the US average in 2010.[76] One reason for this may have been a sharp increase among drug-impaired drivers involved in fatal traffic crashes[60,77]. Drugged driving in the US has become an important traffic safety threat in recent years.[78] Driving a motor vehicle is a complex task, and prescription drug use may impair cognitive and psychomotor skills necessary for the safe operation of a motor vehicle.[58,77,79]. In 2010, 11.4% of all drivers involved in fatal motor vehicle crashes tested positive for drug use.[77] The existing literature shows that the use of prescription opioids, in particular, is associated with an increase in crash risk.[60,77,80] Drivers who used prescription opioids are more than twice as likely as other drivers to be involved in a motor vehicle crash.[80]

The prescription opioid epidemic has been a serious issue in Florida. The average number of prescriptions dispensed annually per person increased from 7.8 per person to 12.6 per person. From 2010 to 2012 in Florida, 1,526 high-risk prescribers were responsible for 67% of total opioid vloume.[81] For the first half of 2010, oxycodone prescriptions in Florida exceeded oxycodone prescriptions in all other states combined.[82] One of the most important steps to control the prescription drug epidemic are PDMPs, which record prescribing substance information for each patient in an online database system accessible by clinicians with prescribing authority.[83] In September 2011, Florida's PDMP program became operational.[66] Prescribers, dispensers, and program officials have access to this database and are able to check patients prescribing histories and make their prescribing decision based on the available information. Further, participation in Florida's PDMP by prescribers and dispensers is mandatory. They should conduct a query for each patient and update patients' information by no longer than the next business day.

Our findings were consistent with the results of previous studies that reported that PDMP implementation had a significant effect on reducing opioid prescribing and opioid-related mortality in Florida.[68,84] After PDMP implementation in Florida, healthcare providers accessed the PDMP at a rapid rate,[68] and a change in prescribing behavior habits occurred that reduced prescribing rates.[85] Delcher et al. reported 92 queries per healthcare provider four months after the PDMP implementation in Florida.[68] Another study reported eighty percent of Florida counties experienced a decrease in opioids prescriptions per capita from 2010 to 2015 because of the PDMP implementation.[86] Previous studies found that prescription opioids are associated with increased risk of fatal crash involvement which is consistent with our finding on opioids.[60,80,87]. Interestingly, despite possible concerns over substitution of illicit drugs in response to decreased availability of prescription opioids, we did not find any differences in the number of heroin, cocaine, or marijuana-related vehicle crash fatalities before and after PDMP implementation.

Our study should be interpreted in the context of certain limitations. Although we adjusted for monthly unemployment, gasoline consumption, and prices, there may be other omitted variables that are significantly associated with monthly crash fatalities. High unemployment rates would lead to less motor vehicle travel and also less vehicle crash fatality.[88,89] Gasoline prices also can change in vehicle miles traveled. [90] We also used gasoline motor fuel consumption as a proxy for vehicle miles traveled. However, coefficients for these variables were not statistically significant. Unfortunately, monthly data on vehicle miles traveled were not available, and demographic variables were either not available monthly or did not have significant monthly variation in our study period. In our negative binomial regression analysis, we also adjusted for the month of the crash to help mitigate these issues. In addition, in our study, drivers were eligible for inclusion regardless of whether prescription opioids were the primary impairment at the time of the crash, which might underestimate the role of other factors as the main cause of the crashes, such as multi-drug combinations and alcohol.

## Conclusions

To our knowledge, our study is the first to analyze the effect of a state PDMP on drug-related fatal crashes. We specifically investigated the effect of PDMP on the presence of prescription opioids on fatal crashes in Florida. We conducted our study using a census-level database of all fatal crashes on public roadways. Our study suggests that PDMP is an effective public health tool to address the adverse effects of the opioid epidemic on traffic safety, although the impact of PDMPs on fatal crashes is not uniform across all drugs.  Our results show that, in addition, to mitigating excessive prescribing of opioids and other drugs, PDMPs are likely to have had a beneficial impact on improving traffic safety.

# CHAPTER 3: IMPACT OF FLORIDA'S PRESCRIPTION DRUG MONITORING PROGRAM ON DRUG-RELATED FATAL VEHICLE CRASHES: A DIFFERENCE-IN-DIFFERENCES APPROACH

## Introduction

The overall use of prescription drugs has increased among US adults over the last two decades.[91-93] Prescription drugs especially, opioids and Central Nervous System (CNS) depressants can impair the functioning of motor skills that are essential for the safe operation of a motor vehicle[94,95] and significantly increase the risk of fatal crash involvement.[77,94,96] The prevalence of prescription opioid use in drivers who died in fatal crashes increased from 1% to 7% between 1995 and 2015 in the US.[60,77] Motor vehicle injuries along with drug overdoses are the leading causes of unintentional injury death.[97,98]

Florida has been one of the epicenters of the opioid epidemic. In 2010, 90 of the top 100 oxycodone purchasing physicians and 49 of the top 50 oxycodone-dispensing clinics in the US were located in Florida.[99] Also, drugged driving has been an important traffic safety issue in the US and especially in Florida.[78] Our analysis of the FARS data show that, in 2010, nearly 5% and 10% of vehicle crash fatalities in Florida involved a driver who tested positive for prescription opioid and all prescription drugs, respectively.[69] From 2001 to 2013, 52% of all drug-related fatalities in Florida were unintentional (e.g., motor vehicle crashes, falls, drowning).[100]

In September of 2011, Florida implemented a mandatory Prescription Drug Monitoring Program (PDMP) for both prescribers and dispensers to help address its prescription drug epidemic.[101] Under a PDMP, prescribers and dispensers have access to online systems that enable them to check patient information, such as the number and type of prescriptions, and identify high-risk individuals based on their prescription history and preventing drug interactions.[10,102] Additionally, PDMPs help prescribers identify individuals who visit multiple prescribers and dispensers to obtain prescriptions (referred to as "doctor shopping") and restrict drug diversion and reduce misuse-related harms including drug-related fatal crashes.[63,102] The success of the PDMPs heavily depends on the legal characteristics of the PDMPs. States that mandated the utilization of the PDMP for all prescribers, dispensers, and pharmacies might have better control over the prescribed drugs. Also, the frequency of updating the patient records on the PDMP system is an essential factor and limits high-risk individuals' access to prescribed drugs. Updated data collection within the PDMP system varies among states and range from the point of sale to up to 14 days. Florida has mandatory query of the PDMP by prescribers and dispensers, and they should update the system no longer than the next business day.[103] Only one year after PDMP implementation in Florida, 18,000 prescribers registered with the PDMP, and 2.3 million queries of the PDMP system were reported.[104]

Recent research found that Florida's PDMP was associated with a 1.4% decrease in opioid prescriptions and a 2.5% decrease in opioid volume one year after PDMP implementation.[57] Another study reported a significant decline in diversion rates for prescription drugs such as oxycodone, methadone, morphine, and hydrocodone after Florida's PDMP implementation. From the first quarter of 2010 to the third quarter of 2012, oxycodone and hydrocodone diversion rates decreased from 49.8 per 100,000 population to 7.6, and from 21.2 per 100,000 population to 5.4, respectively.[38] After the PDMP was implemented, oxycodone-caused mortality also declined by 25% in Florida.[68]

While research has focused on the effect of the PDMP implementation in Florida on opioid prescriptions and diversion, the impact of PDMP on drug-related fatal vehicle crashes remains unknown. To address this research gap, we utilize a difference in differences approach to analyze a census-level database of fatal crashes on Florida roadways to evaluate the impact of its PDMP implementation on prescription drug-related crashes compared to a neighboring state, Georgia, which did not implement a PDMP.

## Methods

### Study Setting and Design

This retrospective longitudinal study included drivers involved in fatal vehicle crashes on public roadways who tested positive for prescribed drugs. To determine the change of drug-related fatal vehicle crashes in the state of Florida attributable to the PDMP implementation, we compared the number of drug-related fatal vehicle crashes in Florida (the treatment group) and Georgia (the control group) before and after PDMP implementation.

We chose Georgia as the control group because it shares many similarities with Florida. The states are neighbors and are similar in size and weather patterns. Commuting characteristics in Florida and Georgia are almost identical, and their population's socio-demographic makeup (e.g., education, income, and poverty rate) is also comparable (Appendix Table A3. 1).[105] Moreover, Georgia did not have an operational PDMP during the analysis period.

### Study Sample and Data

We used the Fatality Analysis Reporting System (FARS) database, which is a nationwide, annual census-level database of all fatal crashes occurring on US public roadways.[69] FARS is compiled by the US National Highway Traffic Safety Administration (NHTSA) using data from crash scene investigations reported by each state. FARS provides detailed information on each crash including location, vehicle characteristics, driver characteristics, crash victims, and toxicology data. However, there are limitations and complexities on drug drug-involved driving in the FARS dataset. From 2008 to 2012, half of drivers involved in fatal motor vehicle traffic crashes were not tested for drugs in the US. In general, testing rates in FARS are higher for drivers who died in crashes. In addition, the FARS dataset informs only about drug presence but not the concentration of a prescription drug, therefore, testing positive does not necessarily mean impaired by the drug, and policies or procedures for testing procedures may vary across states.[106] The percentage of drug testing of fatally injured drivers varies widely among the states. We examined all fatal crashes in which drivers tested positive for prescribed drugs in toxicological testing conducted by the states of Florida and Georgia for drivers suspected of drugged driving. In 2009, 58% and 52% of drivers involved in fatal motor vehicle traffic crashes were tested for drugs in Florida and Georgia.[107] Both states report no drivers with unknown testing status.

We included prescription drugs such as opioids, CNS depressants, or stimulants in the analysis. We conducted the analysis for all prescription drugs and then repeated it for each category (i.e., opioids, CNS depressant, and stimulant). The main outcome of the study was the number of monthly fatal motorized vehicle crashes where a driver involved tested positive for prescription drugs in blood and/or urine in toxicological testing. Moreover, it is possible that the PDMP may have resulted in a substitution of prescription drugs for illicit drugs such as cocaine, marijuana, or heroin. We conducted sensitivity analyses and included these schedule-I drugs.

We included data from January 1, 2009 to June 30, 2013 (right before the implementation of PDMP in Georgia in July 2013). Hence, our data include fatal crashes in the 32 months before and 22 months after Florida's PDMP implementation in September 2011. In total, 990 prescription drug-related vehicle crashes were reported in Florida during the course of the analysis. This includes 606 cases before and 384 cases after Florida's PDMP implementation. In Georgia, 482 prescription drug-related fatal vehicle crash were reported, including 274 crashes before and 208 crashes after Florida's PDMP implementation (see Figure 3. 1).

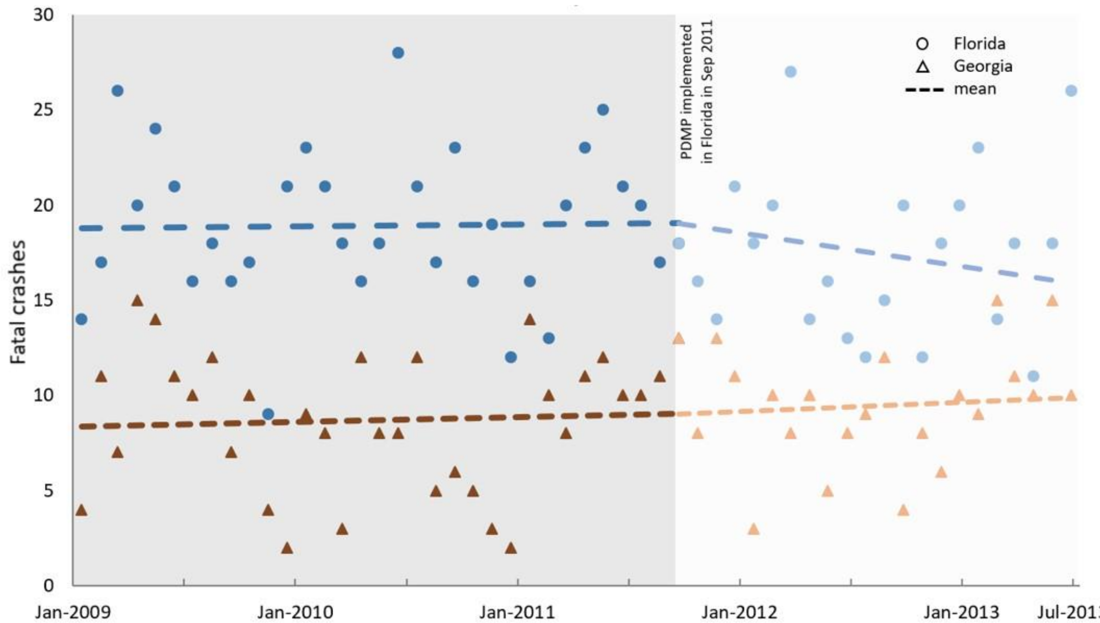



**Figure 3. 1:** Average Prescription Drug-related Vehicle Crashes in Florida and Georgia Before and After PDMP Implementation in Florida

We used drug-related vehicle crash counts as the main analysis input. To ensure that our count-based analysis is robust, we investigated vehicle miles traveled in both states as well as changes in monthly populations over time. We used monthly gasoline consumption obtained from the US Department of Transportation as a proxy for vehicle miles traveled in Florida and Georgia.[73] Appendix Figure A3. 1 shows that slopes of vehicle miles traveled trends were the same in both states. We also inquired about potential policies implemented during the time of this analysis. We used the national population estimates to calculate drug-related vehicle crash rates. [108,109] Additional sensitivity analyses were conducted using population-based rates to control for population changes—the results were similar (see Results section); hence count is a robust unit of measure during the course of this analysis.

**Statistical Analysis**

We used difference-in-differences (DID) regression analysis to estimate the difference in prescription drug-related fatal crashes in Florida. The DID methodology is a quasi-experimental design that is widely used to examine the causal impact of health policies and interventions.[110] It is a rigorous method when attention is focused on specification choice. We followed the checklist proposed for DID analysis to validate the accuracy of estimates in the DID model.[111] Additionally, we conducted further sensitivity analyses using negative binomial regression.

We defined an indicator variable for pre- versus post-PDMP implementation. This was assigned a value of zero and one for before and after Florida's PDMP implementation, respectively. We also defined another indicator variable that was assigned a value of one if the crash occurred in Florida and a value of zero if the crash occurred in Georgia. The analyses were conducted in 2020 using Stata SE 15.1 (College Station, TX) statistical package.

## Results

Figure 1 shows average prescription drug-related fatal vehicle crashes in Florida and Georgia before and after PDMP implementation in Florida (September 2011). A difference in trends in the data was not statistically significant between Florida and Georgia prior to September 2011, and thus the parallel trends assumption required for the DID analysis was not rejected. Data period selection confirms that data exist on the study outcomes before and after the policy implementation for both treatment and control groups. We also performed the Dickey–Fuller test to make sure the baseline outcome levels were unrelated to expectations of changes over time. A Breusch and Pagan test confirmed that standard statistical assumptions were appropriately addressed, and study outcomes are homoscedastic.

Results from the DID analysis are presented in Table 3. 1. The results suggest that PDMP implementation in Florida was associated with lower opioid-related monthly vehicle crashes (−2.21; 95%CI: −4.04 to -0.37; $P<0.05$). Thus, the PDMP resulted in two fewer monthly opioid-related fatal crashes in Florida. While prescription CNS depressant-related vehicle crashes were marginally decreased at $P<0.1$ level (−1.86; 95%CI: −3.48 to -0.23), no significant changes were observed in all categories or stimulants.

**Table 3. 1:** DID Model Results for Prescription Drug-related Fatal Vehicle Crashes Pre- and Post-PDMP Implementation in Florida Compared with Georgia[a]

| Variable | Monthly fatal crashes[b] | | | |
|---|---|---|---|---|
| | All categories | Opioids | CNS depressant | Stimulant |
| **Before PDMP implementation (Jan 2009-Aug 2011)** | | | | |
| Control: Georgia | 8.56 | 3.47 | 4.88 | 2.97 |
| Treated: Florida | 18.94 | 8.31 | 9.69 | 7.13 |
| Treatment-control difference (*A*) | 10.38*** | 4.84*** | 4.81*** | 4.16*** |
| **After PDMP implementation (Sep 2011-Jun 2013)** | | | | |
| Control: Georgia | 9.45 | 4.05 | 4.91 | 3.87 |
| Treated: Florida | 17.45 | 6.68 | 7.86 | 7.41 |
| Treatment-control difference (*B*) | 8.00*** | 2.64*** | 2.95*** | 3.54*** |
| **Difference in differences** | | | | |
| (*B* - *A*) | -2.38 | -2.21** | -1.86* | -0.62 |
| [95% Conf. Interval] | [-5.34, 0.59] | [-4.04, -0.37] | [−3.48, -0.23] | [-2.50, 1.28] |

[a] Linear regression model estimates are based on the data from the Fatality Analysis Reporting System (FARS) database. We included fatal crashes in which drivers tested positive for prescribed drugs in toxicological testing.

[b] ***$p$<0.01, **$p$<0.05, and *$p$<0.10

We repeated the DID analysis using negative binomial regression because the outcome is a count variable. Results were substantively the same as those acquired using the linear DID model (see Appendix Tables A3. 2-A3. 4), building more confidence in our DID analysis.

We also examined illicit drug-related fatal crashes and found no statistically significant difference in the number of cocaine-related vehicle crashes before and after PDMP implementation. We found a marginal decrease in the number of marijuana-related crashes at the marginal significance level of $P<0.1$ (see Appendix Table A3. 5). There were not enough observations to conduct the analysis for heroin-related vehicle crashes.

In addition, we repeated the DID analysis using per capita rates of prescription drug-related vehicle crashes (see Appendix Table A3. 6). The results were similar to those of the count-based DID, indicating that PDMP implementation in Florida was associated with lower prescription opioid-related vehicle crash rates (-0.014 fatal crashes per 100,000 population; 95%CI: -0.028 to -0.0277; $P<0.05$), which is approximately equal to 2.7 fewer monthly fatal crashes. It should be noted that the marginal decrease in CNS depressant at $P<0.1$ (Table 1) were not observed in our rate-based sensitivity analysis (Appendix Table A3. 6). Finally, we repeated the analyses using number of fatalities instead of number of fatal crashes, but results did not substantively change (Appendix Table A3. 7).

## Discussion

Our analysis examined the impact of PDMP implementation on prescription drug-related fatal vehicle crashes on public roads in Florida. Our results showed that PDMP implementation in Florida was associated with approximately two fewer prescribed opioid-related vehicle crashes per month when compared with Georgia, which did not have an operational PDMP during the study period. However, we found no statistically significant differences in CNS depressant, stimulant, or all drug-related fatal crashes pre- and post-PDMP.

Our findings were consistent with the results of another study that explored the impact of the New York prescription drug monitoring program, known as Internet System for Tracking Over-Prescribing (I-STOP). They found that the number of opioid prescriptions declined following the implementation of the I-STOP program.[112] Other studies in Florida also reported a significant reduction in the number of opioid prescriptions and opioid-related mortalities after PDMP implementation.[68,86] Little is known about the impact of Florida's PDMP implementation on prescription drugs other than opioids, but our study suggests a differential impact of the PDMP on opioid-related crashes versus other drug-related crashes. More research is needed to explore reasons for this differential impact.

From 2010 to 2015, 80% of counties in Florida reported a decrease in the number of opioid prescriptions per capita.[86] It is feasible that restricting of access to frequently misused prescribed medications may result in substitution with illicit drugs such as heroin, cocaine, or marijuana.[113,114] However, our analysis did not indicate any significant change (at 0.05 significance level) in drugged driving fatal vehicle crashes due to these potential substitute drugs.

This study is subject to limitations. We included drivers who tested positive for prescribed drugs involved in fatal vehicle crashes without distinction as to whether or not the drug itself caused the vehicle operator any impairment leading to the crash. Unlike alcohol-impaired driving, there are no established, consistent criteria for identifying drug-impaired driving. However, it is well researched that drug use (including the use of opioids, CNS depressants, and stimulants) is associated with a significantly increased risk of fatal crash involvement,[96] therefore, we assumed that a positive drug test result is likely to contribute to the impairment of a motor vehicle operator. There were not enough observations to stratify and analyze age and sex-specific crash rates. Finally, our study does not stratify multi-drug combinations and concurrent use of alcohol as associated factors for crashes, and therefore our findings may be conservative estimates of the impact of the PDMP. Future research is needed to examine the impact of PDMPs on traffic crashes involving alcohol or multi-drug use.

The overall number of car crash fatalities from all causes decreased by 6% and 8.7% from 2009 to 2013 in Florida and Georgia, respectively.[115,116] We chose Georgia as the control group for the DID analysis because Georgia is geographically proximate to Florida and has similar population socio-demographics and commuting characteristics; but Georgia did not have a PDMP in place during the study period. Thus, the use of Georgia for the DID analysis allows the estimation of a counterfactual trend in fatal vehicle crashes for Florida in the absence of the PDMP. We also studied potential policies implemented during the time of this analysis. For example, the DEA crackdown on pill mills started in Florida in February 2010,[117] but during the following 19 months until the implementation of PDMP (Feb-2010 to Sep-2011), the slopes of the average lines for prescription drug-related fatal vehicle crashes in Florida and Georgia remain the same (see Figure 1). However, possible unobserved changes in state policies that significantly impacted traffic safety in either Florida or Georgia post-PDMP may have affected the DID estimates.

Finally, the economic cost of vehicle crashes such as the loss of productivity, medical costs, and property damages, is approximately two percent of the total US domestic product.[118] Therefore, empirical studies evaluating the cost-effectiveness of PDMP implementation are warranted. Future research can also investigate the generalizability of our findings by conducting similar analyses in other states. Moreover, given that the opioid crisis is a multi-layer complex public health problem,[119] further research can employ systems science methods such as simulation modeling to not only project the future effects of policy scenarios,[120] but also conduct economic evaluation of these policies.[121]

## Conclusions

PDMP implementation in Florida resulted in two fewer monthly opioid-related fatal vehicle crashes on public roads (24.8% decrease) and a marginal decrease in prescription CNS depressant-related vehicle crashes. Also, no significant changes were observed in all categories, stimulants and illicit drugs. Our findings suggest that PDMPs policies may have essential secondary benefits in improving public health outcomes such as traffic safety in response to the prescription drug misuse in the US.

# DISCUSSION

## Discussion

This study systematically reviewed the literature and evaluated the effects of PDMP on prescribed drug abuse, misuse, overdose, and unintended negative consequences. Additionally, this study explored the association between different PDMP administrative features and implementation characteristics with rates of abuse and misuse. PDMPs are the most important policies to control the prescription drug epidemic in the U.S. PDMPs enable prescribers (i.e., physicians, physician assistants, and nurse practitioners) and dispensers (i.e., pharmacists) to access an online database that records individuals prescribing substance information and patient behaviors. They can make their prescribing decision based on the available information.[8]

Our systematic review results suggest that mandatory PDMP may change patient and prescriber behavior and is associated with a significant decrease in prescription drug abuse,[35] prescription opioid and stimulant quantities,[32,46] overdose deaths,[32,35,46] and patient extreme utilization behaviors.[32,48] Also, PDMP implementation was associated with decreased illegal drug abuse (e.g., cocaine and heroin).[35,46,48]

As a result of the increase in prescription drug pandemic, drugged driving has increased and has become an important traffic safety and public health concern in the U.S. within the last two decades.[78] Between 2008 to 2012, more than 2,500 people have died in motor vehicle crashes in Florida each year,[76] and the sharp increase in drug-impaired drivers involved in fatal traffic crashes may be an important reason for that.[60,77] Florida's PDMP program became operational in 2011,[66] to combat prescription drugs issue in Florida. Our results suggest that PDMP implementation in Florida was associated with an approximately 20 percent decrease in prescription opioid-related vehicle crashes per month (i.e., two fewer vehicle crashes) than

Georgia, which did not have an operational PDMP by the time of the study. Previous studies confirm that prescription drugs, specifically opioids, increase the risk of fatal vehicle crash involvement.[60,80,87]

Our findings were also consistent with the study results that investigated the impact of the New York PDMP (i.e., I-STOP) that reported a decline in the number of opioid prescriptions after the I-STOP implementation.[112] Other studies focused on Florida's PDMP reported that eighty percent of Florida counties experienced a decrease in opioids prescriptions per capita from 2010 to 2015,[86], which means PDMP implementation significantly reduced prescription opioid-related mortality in Florida.[68,84]

Little is known about the broad impact of the PDMPs on illicit drugs. However, It is possible that individuals who frequently misused prescribed drugs may substitute them with illicit drugs such as heroin, cocaine, or marijuana because of lack or restricted access to prescription drugs after PDMP implementation.[113,114] However, our analysis did not show any significant change in illicit drug-related fatal vehicle crashes involvement due to drug substitution. More research is needed to explore this substitution impact.

Our study should be interpreted in the context of certain limitations. Although we adjusted for monthly unemployment, gasoline consumption (as a proxy for vehicle miles) traveled, and prices, other omitted variables may significantly be associated with prescription drug-related vehicle fatal crashes. In addition, in our study, we included drivers who tested positive for prescribed drugs involved in fatal vehicle crashes regardless of whether prescription opioids were the primary source of impairment at the time of the crash. This inclusion criterion may underestimate the role of other factors such as multi-drug combinations and alcohol use as the primary cause of involvement in fatal vehicle crashes. However, previous studies have found that prescription drug use (e.g., opioids, CNS depressants, and stimulants) is associated with an increased risk of fatal vehicle crash involvement.[96] We also explored potential traffic-related policies implemented during this analysis that might impact fatal vehicle crashes in Florida. However, there might be possible unobserved changes in state policies that affected traffic safety.

## Conclusions

PDMPs appear to hold great potential to combat the prescription drug epidemic in the U.S. if they are designed and used effectively. Our study also suggests that PDMP is an effective public health tool to address the adverse effects of the opioid epidemic and may have vital secondary benefits in improving public health outcomes such as traffic safety. PDMPs have evolved during the last decade, and several states have mandated PDMP enrollment and query that makes the PDMPs more effective and robust. However, finding of possible solutions for the current PDMP barriers (e.g., access difficulties, complicated operating process, and lack of interstate data sharing) could make the PDMPs more effective and user-friendly.

In 2012 the SAMHSA took a big step toward integrating and expanding PDMP data and interstate data sharing through its PDMP Electronic Health Records (EHRs) Integration and Interoperability Expansion (PEHRIIE) program. Also, currently, many states have live-connection and share PDMP Data via RxCheck Hub. These initiatives and actions will increase the use and effectiveness of PDMPs and reduce prescription drug misuse and overdose, and prescription drug-related mortality. Finally, the effectiveness of penalties for not using mandatory PDMPs is unclear and warrants further research. Entailing serious consequences for failure to appropriately use PDMPs (e.g., financial or criminal penalties, loss of licensure or suspension) may increase the use of PDMPs among prescribers and dispensers.

## REFERENCES


1. Zgierska A, Miller M, Rabago D. Patient satisfaction, prescription drug abuse, and potential unintended consequences. *Journal of the American Medical Association.* 2012;307(13):1377-1378.
2. Kunins HV, Farley TA, Dowell D. Guidelines for opioid prescription: why emergency physicians need support. *Annals of Internal Medicine.* 2013;158(11):841-842.
3. Substance Abuse and Mental Health Services Administration. *Results from the 2010 national survey on drug use and health: summary of national findings* Substance Abuse and Mental Health Services Administration;2011.
4. Lipari RN, Hughes A. Nonmedical use of prescription-type drugs, by county type. In: *The CBHSQ Report.* Substance Abuse and Mental Health Services Administration (US); 2013.
5. Warner M, Chen LH, Makuc DM, Anderson RN, Miniño AM. Drug poisoning deaths in the United States, 1980-2008. *NCHS Data Brief.* 2011(81):1-8.
6. MSI MSI. Substance Abuse and Mental Health Services Administration. 2013.
7. Scholl L, Seth P, Kariisa M, Wilson N, Baldwin G. Drug and opioid-involved overdose deaths—United States, 2013–2017. *Morbidity and Mortality Weekly Report* 2019;67(5152):1419.
8. Thomas CP, Kim M, Nikitin RV, Kreiner P, Clark TW, Carrow GM. Prescriber response to unsolicited prescription drug monitoring program reports in Massachusetts. *Pharmacoepidemiology and Drug Safety.* 2014;23(9):950-957.
9. Prescription Drug Monitoring Program Training and Technical Assistance Center. The Goals of Prescription Monitoring. Prescription Drug Monitoring Program Training and Technical Assistance Center http://www.pdmpassist.org/pdf/Prescription_Monitoring_Goals.pdf. Published 2019. Accessed February 11, 2019.
10. Geissert P, Hallvik S, Van JO, et al. High-risk prescribing and opioid overdose: prospects for prescription drug monitoring program-based proactive alerts. *Pain.* 2018;159(1):150-156.
11. Finklea KM, Bagalman E, Sacco LN. Prescription drug monitoring programs. 2014.
12. Prescription Drug Monitoring Program Training and Technical Assistance Center. Prescription Drug Monitoring Programs Administrators' Orientation Package. Prescription Drug Monitoring Program Training and Technical Assistance Center,. http://www.pdmpassist.org/pdf/PDMP_admin/PDMP_Administrators_Orientation_Package_final_20180314.pdf. Published 2018. Accessed February 11, 2019.
13. Prescription Drug Monitoring Program Training and Technical Assistance Center. History of Prescription Drug Monitoring Programs. Prescription Drug Monitoring Program Training and Technical Assistance Center. https://www.pdmpassist.org/pdf/PDMP_admin/TAG_History_PDMPs_final_20180314.pdf. Published 2019 Accessed March 14, 2019.
14. The Prescription Drug Monitoring Program Training and Technical Assistance Center. Mandatory Enrollment And Use of PDMPs. https://www.pdmpassist.org/pdf/TAG_Mandatory_Enrollment_Use_20200710.pdf. Published 2020. Accessed May 25, 2021.

15. Prescription Drug Monitoring Program Training and Technical Assistance Center. PDMP mandatory query by prescribers and dispensers. Prescription Drug Monitoring Program Training and Technical Assistance Center https://www.pdmpassist.org/pdf/Mandatory_Query_20190115.pdf. Published 2019. Accessed April 5, 2019.
16. Prescription Drug Monitoring ProgramTraining and Technical Assistance Center. State PDMP Profiles and Contacts. https://www.pdmpassist.org/State. Published 2021. Updated April 15, 2021. Accessed May 20, 2021.
17. Perrone J, Nelson LS. Medication reconciliation for controlled substances—an "ideal" prescription-drug monitoring program. *New England Journal of Medicine.* 2012;366(25):2341-2343.
18. Gershman JA, Gershman JA, Fass AD, Popovici I. Evaluation of Florida physicians' knowledge and attitudes toward accessing the state prescription drug monitoring program as a prescribing tool. *Pain Medicine.* 2014;15(12):2013-2019.
19. Rutkow L, Turner L, Lucas E, Hwang C, Alexander GC. Most primary care physicians are aware of prescription drug monitoring programs, but many find the data difficult to access. *Health Affairs.* 2015;34(3):484-492.
20. Manasco AT, Griggs C, Leeds R, et al. Characteristics of state prescription drug monitoring programs: a state-by-state survey. *Pharmacoepidemiology and Drug Safety.* 2016;25(7):847-851.
21. Maryland Advisory Council on Prescription Drug Monitoring. Maryland Advisory Council on Prescription Drug Monitoring Legislative Report. Maryland Advisory Council on Prescription Drug Monitoring. http://dhmh.maryland.gov/laboratories/drugcont/docs/Final%20Report%20of%20recommendations%20by%20the%20PDM%20Advisory%20Council%2012-31-09.pdf. Published 2009. Accessed December 31, 2009.
22. Florence C, Luo F, Xu L, Zhou C. The economic burden of prescription opioid overdose, abuse and dependence in the United States, 2013. *Medical care.* 2016;54(10):901.
23. Finley EP, Garcia A, Rosen K, McGeary D, Pugh MJ, Potter JS. Evaluating the impact of prescription drug monitoring program implementation: a scoping review. *BMC health services research.* 2017;17(1):1-8.
24. Nataraj N, Zhang K, Guy Jr GP, Losby JL. Identifying opioid prescribing patterns for high-volume prescribers via cluster analysis. *Drug and Alcohol Dependence.* 2019;197:250-254.
25. Centers for Disease Control and Prevention. State Successes. Centers for Disease Control and Prevention,. https://www.cdc.gov/drugoverdose/policy/successes.html. Published 2019. Accessed May, 2, 2019.
26. Kunins HV, Farley TA, Dowell D. Guidelines for opioid prescription: why emergency physicians need support. *Ann Intern Med.* 2013;158(11):841-842.
27. Abuse S. Mental Health Services Administration, Results from the 2010 National Survey on Drug Use and Health: Summary of National Findings, NSDUH Series H-41, HHS Publication No.(SMA) 11-4658. *Rockville, MD: Substance Abuse and Mental Health Services Administration.* 2011;201.
28. Scholl L, Seth P, Kariisa M, Wilson N, Baldwin G. Drug and opioid-involved overdose deaths—United States, 2013–2017. *Morb Mortal Wkly Rep,.* 2019;67(5152):1419.
29. Zgierska A, Miller M, Rabago D. Patient satisfaction, prescription drug abuse, and potential unintended consequences. *JAMA.* 2012;307(13):1377-1378.

30. Warner M, Hedegaard H, Chen LH. Trends in drug-poisoning deaths involving opioid analgesics and heroin: United States, 1999–2012. 2014.
31. Prescription Drug Monitoring Program Training and Technical Assistance Center. . Prescription Drug Monitoring Programs Administrators' Orientation Package. Prescription Drug Monitoring Program Training and Technical Assistance Center. http://www.pdmpassist.org/pdf/PDMP_admin/PDMP_Administrators_Orientation_Package_final_20180314.pdf. . Published 2019. Accessed February 11, 2019.
32. Buchmueller T, Carey C. The Effect of Prescription Drug Monitoring Programs on Opioid Utilization in Medicare. *Am Econ J.* 2018;10(1):77-112.
33. Dart RC, Reifler LM, Bailey JE, et al. Do Prescription Monitoring Programs Impact State Trends in Opioid Abuse/Misuse? *Pain Med.* 2012;13(3):434-442.
34. Dave DM, Grecu AM, Saffer H. *Mandatory access prescription drug monitoring programs and prescription drug abuse.* National Bureau of Economic Research;2017.
35. Grecu AM, Dave DM, Saffer H. Mandatory Access Prescription Drug Monitoring Programs and Prescription Drug Abuse. *J Policy Anal Manage.* 2019;38(1):181-209.
36. Guy Jr GP, Zhang K, Bohm MK, et al. Vital signs: changes in opioid prescribing in the United States, 2006–2015. *MMWR Morb Mortal Wkly Rep.* 2017;66(26):697.
37. Reifler LM, Droz D, Bailey JE, et al. Do prescription monitoring programs impact state trends in opioid abuse/misuse? *Pain Med.* 2012;13(3):434-442.
38. Surratt HL, O'Grady C, Kurtz SP, et al. Reductions in prescription opioid diversion following recent legislative interventions in Florida. *Pharmacoepidem Dr S.* 2014;23(3):314-320.
39. Alogaili F, Ghani NA, Shah NAK. Prescription drug monitoring programs in the US: A systematic literature review on its strength and weakness. *J Infect Public Health.* 2020.
40. Fink DS, Schleimer JP, Sarvet A, et al. Association between prescription drug monitoring programs and nonfatal and fatal drug overdoses: a systematic review. *Ann Intern Med.* 2018;168(11):783-790.
41. Rhodes E, Wilson M, Robinson A, Hayden JA, Asbridge M. The effectiveness of prescription drug monitoring programs at reducing opioid-related harms and consequences: a systematic review. *BMC Health Serv Res.* 2019;19(1):784.
42. Schuler MS, Heins SE, Smart R, et al. The state of the science in opioid policy research. *Drug Alcohol Depend.* 2020:108137.
43. Moher D, Liberati A, Tetzlaff J, Douglas G. A, and the PG. Preferred. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *Ann Intern Med.* 2009;151(4):264-269.
44. Sterne JA, Hernán MA, Reeves BC, et al. ROBINS-I: a tool for assessing risk of bias in non-randomised studies of interventions. *bmj.* 2016;355.
45. Popovici I, Maclean JC, Hijazi B, Radakrishnan S. The effect of state laws designed to prevent nonmedical prescription opioid use on overdose deaths and treatment. *J Health Econ.* 2018;27(2):294-305.
46. Meinhofer A. Prescription drug monitoring programs: The role of asymmetric information on drug availability and abuse. *Am J Health Econ.* 2018;4(4):504-526.
47. Reisman RM, Shenoy PJ, Atherly AJ, Flowers CR. Prescription Opioid Usage and Abuse Relationships: An Evaluation of State Prescription Drug Monitoring Program Efficacy. *J Subst Abuse Treat.* 2009;3:SART.S2345.
48. Ali MM, Dowd WN, Classen T, Mutter R, Novak SP. Prescription drug monitoring programs, nonmedical use of prescription drugs, and heroin use: Evidence from the National Survey of Drug Use and Health. *Addict Behav.* 2017;69:65-77.

49. Bachhuber MA, Maughan BC, Mitra N, Feingold J, Starrels JL. Prescription monitoring programs and emergency department visits involving benzodiazepine misuse: Early evidence from 11 United States metropolitan areas. *Int J Drug Policy.* 2016;28:120-123.
50. Nam YH, Shea DG, Shi Y, Moran JR. State prescription drug monitoring programs and fatal drug overdoses. *Am J Manag Care.* 2017;23(5):297-303.
51. Pardo B. Do more robust prescription drug monitoring programs reduce prescription opioid overdose? *Addict.* 2017;112(10):1773-1783.
52. Meara E, Horwitz JR, Powell W, et al. State legal restrictions and prescription-opioid use among disabled adults. *N Engl J Med.* 2016;375(1):44-53.
53. Han B, Compton WM, Blanco C, Crane E, Lee J, Jones CM. Prescription opioid use, misuse, and use disorders in US adults: 2015 National Survey on Drug Use and Health. *Ann Intern Med.* 2017;167(5):293-301.
54. Kramarow EA. *Deaths from Unintentional Injury Among Adults Aged 65 and Over, United States, 2000-2013.* HHS, CDC 2015.
55. Control CfD, Prevention. Leading Causes of Injury Death by Age Group Highlighting Unintentional Injury Deaths. *United States-2010.*
56. Control CfD, Prevention. Drug overdose deaths--Florida, 2003-2009. *Morb Mortal Wkly Rep.* 2011;60(26):869.
57. Rutkow L, Chang H-Y, Daubresse M, Webster DW, Stuart EA, Alexander GC. Effect of Florida's prescription drug monitoring program and pill mill laws on opioid prescribing and use. *JAMA Intern Med.* 2015;175(10):1642-1649.
58. Ferreira DH, Boland JW, Phillips JL, Lam L, Currow DC. The impact of therapeutic opioid agonists on driving-related psychomotor skills assessed by a driving simulator or an on-road driving task: a systematic review. *Palliat Med.* 2018;32(4):786-803.
59. Policy OoNDC. Drug Testing and Drug-Involved Driving of Fatally Injured Drivers in the United States: 2005–2009. In: ONDCP, Executive Office of the President …; 2011.
60. Chihuri S, Li G. Trends in prescription opioids detected in fatally injured drivers in 6 US states: 1995–2015. *Am J Public Health.* 2017;107(9):1487-1492.
61. Association GHS. Drug-Impaired Driving: Marijuana and Opioids Raise Critical Issues for States. 2018.
62. Association AP. Pharmacists' role in addressing opioid abuse, addiction, and diversion. *J Am Pharm Assoc.* 2014;54(1):e5-e15.
63. Finklea KM, Bagalman E, Sacco LN. *Prescription drug monitoring programs.* Washington (DC): Congressional Research Service.; 2014.
64. Fla Stat §458.3265.
65. Florida Office of the Attorney General. Florida's prescription drug diversion and abuse roadmap 2012–2015. 2012.
66. §893.055 FS.
67. Florida Department of Health. 2011-2012. Prescription Drug Monitoring Program annual report. http://www.floridahealth.gov/statistics-and-data/e-forcse/news-reports/_documents/2011-2012pdmp-annual-report.pdf. Published 2012. Accessed February 25, 2020.
68. Delcher C, Wagenaar AC, Goldberger BA, Cook RL, Maldonado-Molina MM. Abrupt decline in oxycodone-caused mortality after implementation of Florida's Prescription Drug Monitoring Program. *Drug Alcohol Depend.* 2015;150:63-68.

69. National Highway Traffic Safety Administration. Fatality Analysis Reporting System (FARS). https://www-fars.nhtsa.dot.gov/Main/index.aspx. Published 2019. Accessed October 24, 2019.
70. Prescription Drug Monitoring Program Training and Technical Assistance Center. PDMP Maps and Tables. Prescription Drug Monitoring Program Training and Technical Assistance Center. http://www.pdmpassist.org/content/pdmp-maps-and-tables. Published 2019. Accessed March 14, 2019.
71. US Department of Labor. The Local Area Unemployment Statistics (LAUS),. https://www.bls.gov/lau/. Published 2020. Accessed 30 March, 2020.
72. US Energy Information Administration. Weekly Retail Gasoline and Diesel Prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_a_epm0_pte_dpgal_m.htm. Published 2020. Accessed March 30, 2020.
73. US Department of Transportation. Monthly gasoline/gasohol reported by states. https://www.fhwa.dot.gov/policyinformation/motorfuelhwy_trustfund.cfm. Published 2020. Accessed March 30, 2020.
74. Anastasopoulos PC, Mannering FL. A note on modeling vehicle accident frequencies with random-parameters count models. *Accid Anal Prev.* 2009;41(1):153-159.
75. Chang L-Y. Analysis of freeway accident frequencies: negative binomial regression versus artificial neural network. *Saf Sci.* 2005;43(8):541-557.
76. Chance Scott M, Sen Roy S, Prasad S. Spatial patterns of off-the-system traffic crashes in Miami–Dade County, Florida, during 2005–2010. *Traffic Inj Prev.* 2016;17(7):729-735.
77. Wilson FA, Stimpson JP, Pagán JA. Fatal crashes from drivers testing positive for drugs in the US, 1993–2010. *Public Health Rep.* 2014;129(4):342-350.
78. Brady JE, Li G. Prevalence of alcohol and other drugs in fatally injured drivers. *Addiction.* 2013;108(1):104-114.
79. Lundy J. Kaiser Family Foundation: Prescription Drug Trends. In:2010.
80. Chihuri S, Li G. Use of prescription opioids and motor vehicle crashes: a meta analysis. *Accid Anal Prev.* 2017;109:123-131.
81. Chang H-Y, Lyapustina T, Rutkow L, et al. Impact of prescription drug monitoring programs and pill mill laws on high-risk opioid prescribers: a comparative interrupted time series analysis. *Drug Alcohol Depend.* 2016;165:1-8.
82. Policy OoNDC. *Fact sheet: prescription drug monitoring programs, .* April 2011.
83. Thomas CP, Kim M, Nikitin RV, Kreiner P, Clark TW, Carrow GM. Prescriber response to unsolicited prescription drug monitoring program reports in Massachusetts. *Pharmacoepidem Dr S.* 2014;23(9):950-957.
84. Johnson H, Paulozzi L, Porucznik C, Mack K, Herter B. Hal Johnson Consulting and Division of Disease Control and Health Promotion, Florida Department of Health. Decline in drug overdose deaths after state policy changes—Florida, 2010–2012. *MMWR Morb Mortal Wkly Rep.* 2014;63(26):569-574.
85. Baehren DF, Marco CA, Droz DE, Sinha S, Callan EM, Akpunonu P. A statewide prescription monitoring program affects emergency department prescribing behaviors. *Ann Emerg Med.* 2010;56(1):19-23. e13.
86. Johnson H, Paulozzi L, Porucznik C, Mack K, Herter B. Decline in drug overdose deaths after state policy changes—Florida, 2010–2012. *Morb Mortal Wkly Rep.* 2014;63(26):569-574.
87. Li G, Chihuri S. Prescription opioids, alcohol and fatal motor vehicle crashes: a population-based case-control study. *Inj Epidemiol.* 2019;6(1):11.

88. He MM. Driving through the Great Recession: Why does motor vehicle fatality decrease when the economy slows down? *Soc Sci Med.* 2016;155:1-11.
89. Wagenaar AC. *Unemployment and motor vehicle accidents in Michigan.* (No. UMTRI-83-45 Intrm Rpt.) Technical Report.[12];1983.
90. Chi G, Porter JR, Cosby AG, Levinson D. The impact of gasoline price changes on traffic safety: a time geography explanation. *J Transp Geogr.* 2013;28:1-11.
91. Gu Q. *Prescription drug use continues to increase: US prescription drug data for 2007-2008.* US Department of Health and Human Services, Centers for Disease Control and …; 2010.
92. Kantor ED, Rehm CD, Haas JS, Chan AT, Giovannucci EL. Trends in prescription drug use among adults in the United States from 1999-2012. *JAMA.* 2015;314(17):1818-1830.
93. Schumock GT, Li EC, Suda KJ, et al. National trends in prescription drug expenditures and projections for 2014. *American Journal of Health-System Pharmacy.* 2014;71(6):482-499.
94. C'de Baca J, McMillan GP, Lapham SC. Repeat DUI offenders who have had a drug diagnosis: are they more prone to traffic crashes and violations? *Traffic injury prevention.* 2009;10(2):134-140.
95. Dowell D, Haegerich TM, Chou R. CDC guideline for prescribing opioids for chronic pain—United States, 2016. *JAMA.* 2016;315(15):1624-1645.
96. Li G, Brady JE, Chen Q. Drug use and fatal motor vehicle crashes: a case-control study. *Accid Anal Prev.* 2013;60:205-210.
97. Olaisen RH, Rossen LM, Warner M, Anderson RN. Unintentional injury death rates in rural and urban areas: United States, 1999–2017. *NCHS Data Brief.* 2019(No 343).
98. Rockett IR, Regier MD, Kapusta ND, et al. Leading causes of unintentional and intentional injury mortality: United States, 2000–2009. *Am J Public Health.* 2012;102(11):e84-e92.
99. Florida Board of Medicine. Prescription Drug Monitoring Program. http://flboardofmedicine.gov/latest-news/prescription-drug-monitoring-program-2/. Published 2014. Accessed April 6, 2020.
100. Lee D, Delcher C, Maldonado-Molina MM, Thogmartin JR, Goldberger BA. Manners of death in drug-related fatalities in Florida. *J Forensic Sci.* 2016;61(3):735-742.
101. Prescription Drug Monitoring Program Training and Technical Assistance Center. PDMP Legislation & Operational Dates. https://www.pdmpassist.org/pdf/Legislative_Operational_Dates_20200207.pdf. Published 2020. Accessed December 14, 2019.
102. Rhodes E, Wilson M, Robinson A, Hayden JA, Asbridge M. The effectiveness of prescription drug monitoring programs at reducing opioid-related harms and consequences: a systematic review. *BMC health services research.* 2019;19(1):1-11.
103. PDMP TTAC. State PDMP Profiles and Contacts. PDMP TTAC. https://www.pdmpassist.org/State. Published 2020. Accessed May 1, 2021.
104. Florida Department of Health. Prescription Drug Monitoring Program annual report. http://www.floridahealth.gov/statistics-and-data/e-forcse/news-reports/_documents/2011-2012pdmp-annual-report.pdf. Published 2012. Accessed February 25, 2020.
105. United States Census Bureau. State profile. https://data.census.gov/cedsci/profile?q=United%20States&g=0100000US&tid=ACSDP1Y2018.DP05. Published 2020. Accessed July 17, 2020.

106. Berning A, Smither DD. *Understanding the Limitations of Drug Test Information, Reporting, and Testing Practices in Fatal Crashes: Traffic Safety Facts: Research Note.* United States. Department of Transportation. National Highway Traffic Safety …;2014.
107. Administration NHTS. Drug involvement of fatally injured drivers. *US Department of Transportation Report No DOT HS.* 2010;811:415.
108. Bureau USC. National Population Totals: 2010-2019. https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html. Published 2020. Accessed August 4, 2020.
109. United States Census Bureau. State Intercensal Tables: 2000-2010. https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-state.html. Published 2012. Accessed August 4, 2020.
110. Dimick JB, Ryan AM. Methods for Evaluating Changes in Health Care Policy: The Difference-in-Differences Approach. *JAMA.* 2014;312(22):2401-2402.
111. Ryan AM, Burgess Jr JF, Dimick JB. Why we should not be indifferent to specification choices for difference-in-differences. *Health Serv Res.* 2015;50(4):1211-1235.
112. Brown R, Riley MR, Ulrich L, et al. Impact of New York prescription drug monitoring program, I-STOP, on statewide overdose morbidity. *Drug Alcohol Depend.* 2017;178:348-354.
113. Ali MM, Dowd WN, Classen T, Mutter R, Novak SP. Prescription drug monitoring programs, nonmedical use of prescription drugs, and heroin use: Evidence from the National Survey of Drug Use and Health. *Addict Behav.* 2017;69:65-77.
114. Mallatt J. Unintended Consequences of Prescription Monitoring: Policy-Induced Substitution to Illicit Drugs. *Available at SSRN 3418615.* 2019.
115. Administration NHTS. 2010 motor vehicle crashes: Overview. *US Department of Transportation, Washington, DC, Research Note DOT HS.* 2012;811:552.
116. Administration NHTS. 2014 motor vehicle crashes: Overview. *US Department of Transportation, Washington, DC, Research Note DOT HS.* 2016;812:246.
117. Kennedy-Hendricks A, Richey M, McGinty EE, Stuart EA, Barry CL, Webster DW. Opioid Overdose Deaths and Florida's Crackdown on Pill Mills. *Am J Public Health.* 2016;106(2):291-297.
118. Blincoe L, Miller TR, Zaloshnja E, Lawrence BA. *The economic and societal impact of motor vehicle crashes, 2010 (Revised).* 2015.
119. Jalali MS, Botticelli M, Hwang RC, Koh HK, McHugh RK. The opioid crisis: a contextual, social-ecological framework. *Health Res Policy Syst.* 2020;18(1):1-9.
120. Jalali MS, Botticelli M, Hwang RC, Koh HK, McHugh RK. The opioid crisis: need for systems science research. *Health Res Policy Syst.* 2020;18(1):1-5.
121. Beaulieu E, DiGennaro C, Stringfellow E, et al. Economic Evaluation in Opioid Modeling: Systematic Review. *Value Health.* 2020.

# APPENDICES

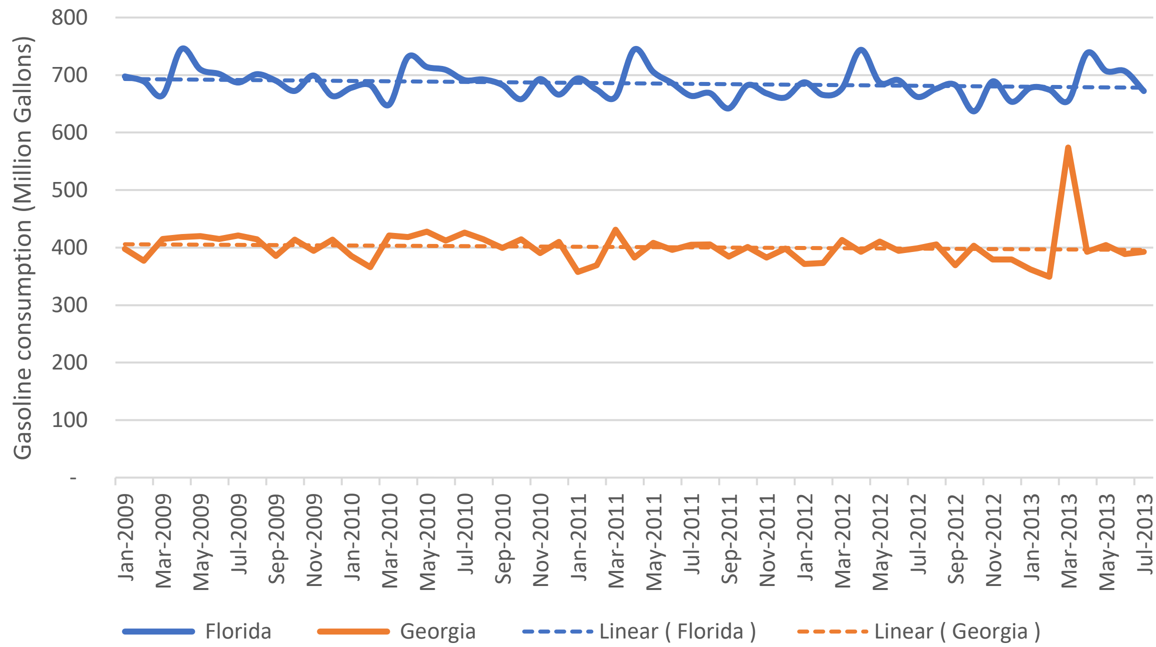



**Figure A3. 1:** Average Monthly Gasoline Consumption in Florida and Georgia Before and After PDMP Implementation in Florida (September 2011)

**Table A2. 1:** Negative Binomial Regression (Gas Price, Gas Consumption, Unemployment, and Month Control) for Prescription Drug-related Vehicle Crash Fatalities Before and After PDMP Implementation in Florida

| Fatals | Coef. | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|
| PDMP | -0.035 | 0.81 | [-0.32 | 0.25] |
| Gas price | 0.018 | 0.82 | [-0.13 | 0.17] |
| Gas consumption | 0.003 | 0.25 | [0.00 | 0.01] |
| Unemployment | 0.014 | 0.70 | [-0.06 | 0.09] |
| _Imonth_2 | 0.034 | 0.81 | [-0.24 | 0.30] |
| _Imonth_3 | 0.305 | 0.04 | [0.01 | 0.60] |
| _Imonth_4 | -0.205 | 0.31 | [-0.60 | 0.19] |
| _Imonth_5 | 0.095 | 0.50 | [-0.18 | 0.37] |
| _Imonth_6 | 0.088 | 0.53 | [-0.19 | 0.36] |
| _Imonth_7 | -0.012 | 0.93 | [-0.29 | 0.27] |
| _Imonth_8 | -0.153 | 0.29 | [-0.43 | 0.13] |
| _Imonth_9 | 0.031 | 0.82 | [-0.24 | 0.30] |
| _Imonth_10 | -0.150 | 0.35 | [-0.46 | 0.16] |
| _Imonth_11 | -0.144 | 0.31 | [-0.42 | 0.14] |
| _Imonth_12 | 0.146 | 0.31 | [-0.14 | 0.43] |
| Constant | 0.623 | 0.77 | [-3.51 | 4.76] |

**Table A2. 2:** Negative Binomial Regression (Month Control) for Prescription Opioids-related Vehicle Crash Fatalities Before and After PDMP Implementation in Florida

| Fatals | Coef. | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|
| PDMP | -0.262 | <0.01* | [-0.44 | -0.09] |
| _Imonth_2 | 0.024 | 0.91 | [-0.40 | 0.45] |
| _Imonth_3 | 0.270 | 0.19 | [-0.13 | 0.67] |
| _Imonth_4 | -0.127 | 0.57 | [-0.57 | 0.32] |
| _Imonth_5 | 0.134 | 0.53 | [-0.28 | 0.55] |
| _Imonth_6 | 0.154 | 0.46 | [-0.26 | 0.57] |
| _Imonth_7 | -0.127 | 0.57 | [-0.57 | 0.32] |
| _Imonth_8 | -0.182 | 0.43 | [-0.63 | 0.27] |
| _Imonth_9 | 0.258 | 0.22 | [-0.15 | 0.67] |
| _Imonth_10 | -0.004 | 0.98 | [-0.44 | 0.43] |
| _Imonth_11 | -0.004 | 0.98 | [-0.44 | 0.43] |
| _Imonth_12 | 0.157 | 0.46 | [-0.26 | 0.57] |
| Constant | 2.068 | <0.01* | [1.76 | 2.38] |

PDMP: prescription drug monitoring program .Statistically significant: *$p$<0.01

**Table A2. 3:** Truncated Negative binomial Regression-adjusted Incidence Rate Ratios (IRR)

| Fatals | IRR | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|
| All drugs | 0.92 | 0.17 | [0.83 | 1.03] |
| Opioids | 0.78 | <0.01* | [0.65 | 0.92] |
| Depressant | 0.80 | <0.01* | [0.68 | 0.93] |
| Stimulant | 1.10 | 0.30 | [0.91 | 1.33] |

Statistically significant: *$p$<0.01

**Table A3. 1:** Socioeconomic and Commuting Characteristics Based on the U.S. Census Bureau's 2018 American Community Survey

| | Florida (n=113,000) | | Georgia (n=51,500) | |
|---|---|---|---|---|
| | **Estimate** | **Margin of Error** | **Estimate** | **Margin of Error** |
| **People and population** | | | | |
| Population (million) | 21.3 | NA | 10.5 | NA |
| Age | | | | |
| Median age (year) | 42.2 | 0.2 | 36.8 | 0.3 |
| Under 5 years (percent) | 5.3 | 0.1 | 6.1 | 0.1 |
| 18 years and older (percent) | 80.2 | 0.1 | 76.2 | 0.1 |
| 65 years and older (percent) | 20.5 | 0.1 | 13.8 | 0.1 |
| **Race and Ethnicity** | | | | |
| White alone (percent) | 74.6 | 0.2 | 58.3 | 0.2 |
| Black (percent) | 16 | 0.1 | 31.6 | 0.1 |
| Asian (percent) | 2.8 | 0.1 | 4.1 | 0.1 |
| Other (percent) | 6.6 | NA | 6 | NA |
| **Education** | | | | |
| High school graduate or higher (percent) | 88.5 | 0.1 | 87.6 | 0.1 |
| **Income and poverty** | | | | |
| Median household income (dollar) | 55,462 | $384 | 58,756 | $711 |
| Poverty rate (percent) | 13.6 | NA | 14.3 | NA |
| Employment (percent) | 55.4 | 0.2 | 59.6 | 0.3 |
| **Commuting** | | | | |
| Average commute to work (minute) | 28 | 0.1 | 29 | 0.2 |
| Means of transportation | | | | |
| Drove alone (percent) | 79.1 | 0.3 | 79.4 | 0.4 |
| Carpool (percent) | 9.4 | 0.2 | 9.4 | 0.3 |
| Public transportation (percent) | 1.7 | 0.1 | 2 | 0.2 |
| Walked (percent) | 1.4 | 0.1 | 1.5 | 0.1 |
| Other means (percent) | 2.4 | 2.4 | 1.5 | 0.1 |
| Worked at home (percent) | 6.2 | 0.2 | 5.9 | 0.2 |

NA, Not Applicable

Notes: Margin of error is defined as the Z-score times the standard error.

**Table A3. 2:** Negative Binomial Regression Coefficients for Prescription Drug-related Fatal Vehicle Crashes After PDMP Implementation in Florida Compared with Georgia

| Drug category* | Fatals | Coef. | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|
| All categories | Florida | 0.794 | <0.01 | [0.65 | 0.94] |
| | Post-PDMP | 0.099 | 0.29 | [-0.08 | 0.28] |
| | Florida Post-PDMP | -0.181 | 0.12 | [-0.41 | 0.05] |
| | Intercept | 2.147 | <0.01 | [2.03 | 2.27] |
| Opioids | Florida | 0.874 | <0.01 | [0.65 | 1.1] |
| | Post-PDMP | 0.154 | 0.28 | [-0.13 | 0.43] |
| | Florida Post-PDMP | -0.372 | 0.03 | [-0.72 | -0.03] |
| | Intercept | 1.244 | <0.01 | [1.06 | 1.43] |
| Stimulant | Florida | 0.875 | <0.01 | [0.63 | 1.12] |
| | Post-PDMP | 0.263 | 0.09 | [-0.04 | 0.57] |
| | Florida Post-PDMP | -0.224 | 0.24 | [-0.60 | 0.15] |
| | Intercept | 1.088 | <0.01 | [0.88 | 1.30] |

*The model was not concave for CNS depressant

**Table A3. 3:** Predictive Margins, Florida with Georgia

| | Coef. | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|
| **State** | | | | |
| Georgia | 3.704 | <0.01 | [3.19 | 4.22] |
| Florida | 7.649 | <0.01 | [6.91 | 8.39] |
| **PDMP** | | | | |
| Pre-PDMP | 5.891 | <0.01 | [5.30 | 6.49] |
| Post-PDMP | 5.364 | <0.01 | [4.68 | 6.05] |
| **Interactions** | | | | |
| Georgia Pre-PDMP | 3.469 | <0.01 | [2.82 | 4.11] |
| Georgia Post-PDMP | 4.046 | <0.01 | [3.21 | 4.89] |
| Florida Pre-PDMP | 8.313 | <0.01 | [7.31 | 9.31] |
| Florida Post-PDMP | 6.682 | <0.01 | [5.60 | 7.76] |

**Table A3. 4:** Predicted Monthly Fatal Crashes From Negative Binomial Regression Modeling of Prescription Drug-related Vehicle Crashes Pre- Versus Post-PDMP Implementation in Florida Compared with Georgia

| Variable | Contrast | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|
| All categories | -2.38 | 0.11 | [-5.29 | 0.54] |
| Opioid | -2.21 | 0.02 | [-4.02 | -0.39] |
| CNS depressant* | NA | NA | NA | NA |
| Stimulant | -0.61 | 0.53 | [-2.50 | 1.28] |

*The model was not concave for CNS depressant

**Table A3. 5:** DID Model Results for Cocaine- and Marijuana-related Fatal Vehicle Crashes Pre- and Post-PDMP Implementation in Florida Compared with Georgia[a]

| Variable | Average Crashes[b] | |
|---|---|---|
| | Cocaine | Marijuana |
| **Before PDMP implementation (Jan 2009-Aug 2011)** | | |
| Control: Georgia | 0.719 | 0.094 |
| Treated: Florida | 4.844 | 2.187 |
| Treatment-control difference (*A*) | 4.125*** | 2.094*** |
| **After PDMP implementation (Sep 2011-Jun 2013)** | | |
| Control: Georgia | 0.955 | 0.913 |
| Treated: Florida | 4.182 | 2.238 |
| Treatment-control difference (*B*) | 3.227*** | 1.325*** |
| **Difference in differences** | | |
| (*B* - *A*) | -0.898 | -0.769* |
| [95% Conf. Interval] | [-2.26, 0.46] | [-1.47,-0.07] |

[a] Linear regression model estimates are based on the data from the Fatality Analysis Reporting System (FARS) database. We included fatal crashes in which drivers tested positive for prescribed drugs in toxicological testing.

[b] ***$p$<0.01, **$p$<0.05, and *$p$<0.10

**Table A3. 6:** DID Model Results for Prescription Drug-related Fatal Vehicle Crash Rates Pre- and Post-PDMP Implementation in Florida Compared with Georgia[a]

| Variable | Crash rates[b,c] | | | |
|---|---|---|---|---|
| | All categories | Opioids | CNS Depressants | Stimulants |
| **Before PDMP implementation (Jan 2009-Aug 2011)** | | | | |
| Control: Georgia | 0.087 | 0.035 | 0.049 | 0.030 |
| Treated: Florida | 0.102 | 0.044 | 0.051 | 0.038 |
| Treatment-control difference (*A*) | 0.014* | 0.009** | 0.003 | 0.008* |
| **After PDMP implementation (Sep 2011-Jun 2013)** | | | | |
| Control: Georgia | 0.095 | 0.040 | 0.049 | 0.039 |
| Treated: Florida | 0.089 | 0.035 | 0.043 | 0.040 |
| Treatment-control difference (*B*) | -0.006 | -0.005 | -0.006 | 0.001 |
| **Difference in differences** | | | | |
| (*B* - *A*) | -0.020* | -0.014** | -0.009 | -0.007 |
| [95% Conf. Interval] | [-0.04,-0.0003] | [-0.03,-0.0003] | [-0.02, 0.01] | [-0.02, 0.01] |

[a] Linear regression model estimates are based on the data from the Fatality Analysis Reporting System (FARS) database. We included fatal crashes in which drivers tested positive for prescribed drugs in toxicological testing.

[b] ***$p$<0.01, **$p$<0.05, and *$p$<0.10

[c] Fatal crash rates calculated as number of *fatal crashes*/*population* X 100,000.

**Table A3. 7:** DID Model Results for Opioid-related Vehicle Crash Fatalities Pre- and Post-PDMP Implementation in Florida Compared with Georgia[a]

| Variable | Average fatalities[b] Opioids |
|---|---|
| **Before PDMP implementation (Jan 2009-Aug 2011)** | |
| Control: Georgia | 4.187 |
| Treated: Florida | 9.281 |
| Treatment-control difference (*A*) | 5.094*** |
| **After PDMP implementation (Sep 2011-Jun 2013)** | |
| Control: Georgia | 4.727 |
| Treated: Florida | 7.091 |
| Treatment-control difference (*B*) | 2.364*** |
| **Difference in differences** | |
| (*B* - *A*) | -2.730** |
| [95% Conf. Interval] | [-5.02, -0.44] |

[a] Linear regression model estimates are based on the data from the Fatality Analysis Reporting System (FARS) database. We included fatal crashes in which drivers tested positive for prescribed drugs in toxicological testing.

[b] ***$p$<0.01, **$p$<0.05, and *$p$<0.10