Flipping the Script: Evaluating the Policy Effects and Restrictiveness of PDMPs on Opioid Prescribing Behavior

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Abstract

Over the past decade, federal and state governments have implemented a variety of policies to address the debilitating effects of the opioid epidemic. One of the most effective tools has been mandatory access Prescription Drug Monitoring Programs (MA-PDMPs), which aim to curb the epidemic at a common point of initiation of use, the prescription. However, there is a recent concern as to whether these opioid specific policies have been too restrictive and reduced appropriate access to patients with the most need for these pharmaceuticals. To answer this question we assess the effect of this mandatory component on specialty-specific opioid prescribing behavior using the CMS Medicare Part D Public Use Files. Our findings suggest that requiring providers to query a PDMP database, prior to prescribing an opioid drug, differentially affects opioid prescribing across provider specialty. As in other studies, we find an overall decrease in prescribing as a result of implementing a MA-PDMP, but find that this decrease is largely driven primarily by primary care and inpatient care providers. Interestingly, we also find *increases* in prescribing for oncology and palliative care providers after a MA-PDMP is implemented. Our results indicate that MA-PDMPs may help close provider-patient informational gaps while retaining a provider's ability to supply these drugs to patients with a need for opioids (e.g. end of life care).

1 Introduction

From 1999 to 2017, the United States saw a 253 percent increase in fatal drug overdoses per capita and a 200 percent increase in the rate of overdose deaths involving opioids [Rudd et al. (2016), SAMHSA (2019)]. State-specific efforts to directly quell negative effects of the epidemic include Naloxone access laws [Rees et al. (2019) and Abouk et al. (2019)], crackdowns on "pill mills" [Meinhofer (2016)], and limits on initial prescription length [Sacks et al. (2019)].[1] However, there is a concern that these recent efforts to restrict opioid prescribing and reduce mortality may have had the unintended consequence of reducing access to

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[1] There have also been state policies that have had indirect benefits such as medical marijuana laws [Powell et al. (2018) and Pacula et al. (2015)] and expanding medicaid eligibility [Grooms and Ortega (2019), Maclean and Saloner (2019) and Snider et al. (2019)].

those individuals who **need** medicine for legitimate reasons [Dalal and Bruera (2019) and Yuanhong Lai et al. (2019)]. For instance, opioids are necessary for many patients with cancer, but the stigma surrounding these drugs and the policies implemented to restrict their access may lead to unintentional reductions in prescribing for these types of patients [Allen et al. (2020)] − particularly when high need patients are not the target of policies aimed at combating the epidemic. Recent literature has suggested that one of the most effective tools at curbing opioid prescribing and doctor shopping are mandatory access prescription drug monitoring programs (MA-PDMP). MA-PDMPs require prescribers to query an electronic database prior to prescribing a controlled substance. This paper examines whether MA-PDMPs have reduced opioid prescribing by providers in all specialties who treat a variety of patients, including those with legitimate need for this type of medication. We use data on over 600,000 U.S. providers and over 500 million prescriptions in Medicare Part D to study the effect of MA-PDMPs on opioid prescribing behavior. Specifically, since the degree of provider-patient informational asymmetry differ across specialties, we estimate heterogeneous MA-PDMP treatment effects by specialty.

Incomplete information on a patient's prescribing history can make *appropriate* prescribing difficult. This information asymmetry can lead to overlapping opioid prescriptions, inconsistent dosing regiments, and greater risks of misuse. Previous work finds that limited access to patient medical and prescription history poses significant concerns in prescribing opioids [e.g. Logan et al. (2013)]. Although the rapid uptake of PDMPs throughout the country may lead some to expect a decline in the number of opioids prescribed for all providers, it is important to note that these programs are intended to decrease prescription opioid misuse through appropriate prescribing based on more complete patient information. This is especially true for PDMPs with a mandate. These policies do not directly target reductions in opioid prescribing among specific providers or for certain groups of patients. Therefore, if the goal of states with stricter PDMPs is to reduce the amount of opioids prescribed generally, these policies may unintentionally reduce opioid prescribing to those who have the highest need for opioids (e.g., end of life care). Further, MA-PDMPs will only have their intended effects across all specialties if this additional patient information enables a provider to make the most informed prescribing decision to patients at the margin. For this reason, we measure heterogeneous effects of MA-PDMP implementation across specialties.

This study contributes to a growing body of literature demonstrating that MA-PDMPs are a useful tool in combating the opioid epidemic. There are three primary contributions of our work. First, we contribute to this literature by using the population of Medicare part D providers to study broad opioid prescribing in response to MA-PDMPs by adequately and rigorously addressing data limitations in this population. Second,

we consider national provider patterns of opioid prescribing which is distinct from other studies examining doctor-shopping [Buchmueller and Carey (2018)] and initial opioid prescriptions [Sacks et al. (2019)]. Third, this is the first study to estimate the heterogeneous effects of MA-PDMPs on changes in opioid prescribing across specialties. This last contribution is vitally important. Information from a query may be illuminating for providers in specialties that see many irregular patients with a wide range of diagnoses, such as primary care or emergency medicine. Conversely, due to the nature of repeated contact with the same patients, in the absence of a PDMP, other types of providers may have more complete information on their patients (e.g. palliative care, oncology). Thus, the information gap that a MA-PDMP fills may result in quantitative and qualitative differences in prescribing.

Our baseline analysis uses a difference-in-differences (DD) and event-study approach to compare the prescribing behavior of Medicare providers in states that implement a MA-PDMP to those in states that do not implement a MA-PDMP. Therefore, our results provide an estimate of the impact of MA-PDMPs on opioid prescribing by provider specialty. We conduct a number of validity checks to support the specification of our study. Our findings suggest considerable differences in opioid prescribing in response to PDMPs across type of specialty. We find that the most common provider types (primary care and inpatient medicine) prescribe fewer opioids once a MA-PDMP is implemented. These physicians decrease prescribing by about 2.3 percent (about 9 fewer prescriptions per year). We do not find a consistent decrease in prescribing for other specialties. In fact, we find an increase in opioid prescribing for oncology and palliative care providers. Our results are robust to a series of robustness checks that adjust exclusion criteria both for providers and for opioid drugs, as well as adjusting for the implementation of other opioid policies that may influence prescribing (e.g. initial prescribing limits). We provide further evidence that the mandatory query is a salient policy to influence opioid prescribing. Our study provides the first evidence that not all providers are impacted homogeneously by MA-PDMPs. These findings may indicate that MA-PDMPs have not led to an unintentional reduction in the access of opioids for patients most in need of these types of pharmaceuticals. Finally, policymakers should consider multiple factors, including the level of informational asymmetry in considering the uptake of a mandated query as part of already broadly implemented PDMPs across the U.S.

2 Background and Related Literature

2.1 Prescription Drug Monitoring Programs (PDMPs)

As early as the 1930s, state regulatory and law enforcement agencies felt a need to establish a system that would facilitate the tracking and monitoring of particular prescription drugs. The initial uptake of such a system was very gradual, with California being the first state to adopt a PDMP in 1939 and only nine other states with a similar program by 1992. Originally, these programs assisted in tracking theft and forgery of prescriptions. However, growing concerns regarding drug misuse coupled with the onset of efficient computer-automated pharmacy practices led to the implementation of PDMP legislation in many more states.[2] As of the end of our study period, 2017, only Missouri and Washington D.C. did not have PDMP legislation. Common goals amongst all PDMPs include the detection and prevention of drug abuse, and supporting the use of controlled substances for appropriate medical purposes. In addition to setting a basic standard, the National Alliance for Model State Drug Laws has also set specific guidelines regarding the characteristics of state PDMPs [Blumenschein et al. (2010)]. Moreover, any entity (e.g. prescribers, dispensers, law enforcement agencies, etc.) that requests information through the program should undergo training that assures appropriate use of a PDMP. Table A1 in the Appendix provides a list of states and the month and year in which their MA-PDMP was implemented. We consider the effects of PDMPs when they become operational, rather than when the legislation is enacted; this is an important distinction given that the time between legislation and implementation ranges from months to years. Using the year the PDMP becomes operational ensures that prescribers can access query results and use information from the PDMP database in their prescribing decisions.

2.2 PDMP Implementation Considerations

In theory, PDMPs aid in the prevention and early detection of opioid use disorder (OUD) and opioid misuse by providing prescribers with more complete patient information on drugs federally classified as controlled substances. There are operational differences among states' PDMPs. One key operational difference is whether prescribers are mandated to query a PDMP prior to providing controlled pharmaceuticals to patients. This turns out to be a salient requirement given that PDMP utilization rates are roughly 50 percent in states where checking a PDMP is voluntary [Excellence (2014)], an important distinction given that almost every state has adopted a PDMP as of 2020. Several studies find that on average, PDMPs have little to no

[2]For detailed information on PDMPs by state see http://www.pdmpassist.org/.

effect on opioid use [Paulozzi et al. (2011), Li et al. (2014), Brady et al. (2014), and Moyo et al. (2017)]. However, recent work demonstrates that there are considerable effects that depend on program characteristics − particularly mandating query [Buchmueller and Carey (2018), Bao et al. (2016), and Dowell et al. (2016b)].

Given the severity of the opioid epidemic in conjunction with the rapid uptake in state PDMPs nationally, it may be easy to conflate the intended goal of improved opioid prescribing with the reduction of opioids prescribed. But these are two distinct outcomes. If the goal of a PDMP is to improve the appropriateness of prescribing, the result of the program need not be fewer opioids prescribed. Prior to the implementation of PDMPs, providers may have been concerned about prescribing opioids due to the extent of the epidemic and concerns about doctor shopping. Therefore, the information offered by PDMP databases may dispel this fear and potentially increase the level of opioid prescribing. Thus, the goal of improving opioid prescribing *may* result in fewer opioids prescribed, but this is different than implementing a PDMP with the targeted purpose of reducing the number of opioids prescribed.

There is growing concern in voluntary states about the frequency with which PDMPs are reviewed prior to issuing a prescription. For instance, some prescribers cite procedural hurdles or minimal guidance in interpreting query results as contributing to lack of use [Haffajee et al. 2015]. In a nationally representative survey, only one in two physicians reported using the program [Rutkow et al. 2015]. This may partly explain why early studies have found that PDMPs have little to no effect on opioid prescriptions and overdose mortality [Paulozzi et al. (2011), Li et al. (2014), Brady et al. (2014),Moyo et al. (2017), and Yarbrough (2017)]. However, recent work by Sacks et al. (2019) suggests that the mandate has negligible effects on initial prescriptions.

Conversely, Bao et al. (2016) finds the probability of a physician prescribing a Schedule II opioid decreases after a state implements a PDMP; however, this study focuses solely on patients seeking emergency care for a pain-related injury. Simeone and Holland (2006) find that states with PDMPs that monitor in a "comprehensive" manner were successful at decreasing the growth rate of opioid sales. Similarly, Reifler et al. (2012) suggests the ability of some PDMPs to successfully mitigate opioid abuse lies in the characteristics of the program. Given this information, some states have instituted mandates to increase PDMP program use, where providers are legally required to query their state's PDMP before prescribing a controlled substance. Providers who fail to comply with a query mandate are subject to penalties as specified by the state and also increase the risk of legal liability if misuse, overdose, or death occurs [Haffajee et al. 2015]. Existing evidence suggests that a query mandate may be an effective tool in curbing the opioid epidemic. To the extent that

a query accurately identifies patients at risk for opioid misuse, it may also prevent adverse events. For instance, Rasubala et al. (2015) find a statistically significant decrease in the number of opioids prescribed by dentists following the implementation of a query mandate in New York. In a study of New Hampshire surgeons, Stucke et al. (2018) find that the presence of the recently legislated MA-PDMP had no significant association with changes in opioid prescribing for patients undergoing general surgical procedures.

Buchmueller and Carey (2018) use data from 2007 to 2013 to examine "extreme utilization" of prescription opioids among Medicare Part D beneficiaries in the presence of a query mandate. Their analysis focuses on patient behavior given the strength of a state's PDMPs, and results suggest that MA-PDMPs significantly reduce doctor shopping behavior. Buchmueller and Carey (2018) focus on a subset of patients who over-use opioids, not the entire Medicare population. In fact, the modal number of opioids prescribed by physicians in their sample is one where the 99th-percentile of prescribers only write scripts to six individuals. Thus, their random sample is best suited for examining the behavior of Medicare enrollees and not the behavior of prescribers. Complimentary to this paper, a recent study by Buchmueller et al. (2019) examines the universe of providers in Kentucky (a "mandatory" state) and Indiana (a "voluntary" state). They find a stark decrease in prescribing as a result of the mandate, particularly among low-volume prescribers. However, the PDMP literature has yet to emphasize provider prescribing behavior or differences in prescriber-patient information asymmetries.

Our paper addresses a substantial void in the literature by considering prescribing differences across specialty, while acknowledging the mandate as a driver of prescribing behavior following PDMP implementation. Given that opioid prescribing trends vary by specialty [Levy et al. 2015], responses to a query mandate are also likely to differ. Further, continuity of care in some areas of medicine, as well as the types of illness or disease a provider treats, may influence both the usefulness of resolving informational asymmetries and a provider's ability to use alternate treatments where opioid use is inadvisable. Thus, we recognize the possibility that prescribers in certain areas of medicine may respond differently to prescribing regulations, and stratify our results by specialty.

2.3 Opioid Prescribing Among the Elderly

Opioid prescribing among the Medicare population itself is of particular interest for several reasons. From 2016 to 2017, the U.S. prescription opioid-involved death rate increased most for those ages 65 and older [Scholl et al. (2019)], a population that itself is fast growing. By 2029 all of the baby boomers will be 65 or over, approximately more than 20 percent of the total U.S. population [Colby and Ortman (2014)].

Older adults take more prescription drugs than younger adults [Kennedy et al. (1999)], which increases the possibility of misuse and/or abuse. Wato et al. (2008) finds that over 36 percent of both elderly men and women used at least five prescription medications at the same time. Moreover, Jena et al. (2014) find that concurrent opioid prescribing among multiple providers is a frequent occurrence among Medicare patients, leading to an increase in opioid-related hospital admissions. Research also indicates that disabled individuals among Medicare Part D beneficiaries may be particularly at risk. Buchmueller and Carey (2018) find that reductions in opioid misuse among Medicare Part D beneficiaries due to MA-PDMPs is mainly driven by disabled individuals, for which opioid use is very prevalent. Morden et al. (2014) claim that about 44 percent of disabled Medicare beneficiaries use opioids.

The providers who prescribe opioids to Medicare patients often serve a diverse panel of patients. A majority of physicians accept patients from both Medicare and private insurance [Boccuti et al. (2015)]. Further, opioid prescribing among the Medicare Part D population tends to match key features in opioid research more broadly. In addition, opioid prescribing among Medicare patients may influence opioid misuse, opioid use disorder, and opioid overdose in the general population. Powell et al. (2020) show that expansions in opioid supply due to the introduction of the Medicare Part D benefit "resulted in an escalation in opioid-related substance abuse treatment admissions and opioid-related mortality among the Medicare-ineligible population," implying meaningful spillover effects of opioids prescribed to Medicare beneficiaries on the health of the general population. Further, many adolescents who misuse prescription pain relievers obtain them for free from a friend or relative [National Institute of Drug Abuse (2015)]. These studies create an imperative to effectively identify the efficacy of policies that address substance use among all populations, including older adults.

3 Data and Methods

3.1 Data Sources

To measure the effect of MA-PDMPs on opioid prescribing, we study the prescribing behavior of 631,727 healthcare providers for Medicare Part D beneficiaries. Data on opioid prescribing was obtained from the Part D Prescriber Public Use Files (PUFs) from the Centers for Medicare and Medicaid Services (CMS) Provider Utilization and Payment Data, which contains information on drugs prescribed by various types of providers and paid for under the Medicare Part D Prescription Drug Program. To verify our findings among Medicare Part D providers, we compare opioid prescribing changes in this population to results found

in other studies with other study populations [e.g. Buchmueller and Carey (2018) and Buchmueller et al. (2019)]. Part D PUFs are compiled from Prescription Drug Event (PDE) records submitted by Medicare Advantage Prescription Drug plans and by stand alone Prescription Drug Plans (PDP). Each year includes PDEs through the cutoff, June 30 of the following year. For example, data from 2015 include PDEs from July 1, 2015 through June 30, 2016. All claims adjustments received through the cutoff date have been resolved. Prescribing data was combined with American Medical Association historical physician data. Prescribing data was also supplemented with data on state PDMPs and state-level demographic information. PDMP mandate implementation dates are available from the Prescription Drug Abuse Policy System [Center for Public Health Law Research (2017)]. Demographic data was obtained from the University of Kentucky Center for Poverty Research [University of Kentucky Center for Poverty Research (2019)]. It includes information on population statistics, workers' compensation, unemployment, and poverty as well as many other state-level demographic variables.

3.2 Study Population

We obtained CMS Part D prescriber public use files (PUFs) from 2010-2017.[3] For each year, the PUFs are compiled from Medicare Part D claims and are organized and aggregated by National Provider Identifier (NPI) and drug name. The CMS Part D PUFs during our study period (2010-2017) are comprised of 697,119 providers[4] throughout the United States. Because of the data construction of the CMS Part D PUFs, a number of exclusionary criteria must be implemented to conduct the analysis presented here. In our final analytic dataset we exclude less than 10 percent of the original sample. We exclude (1) observations without a unique prescriber identifier, either national provider identifier (NPI) or Drug Enforcement Agency (DEA) identifier; (2) providers in U.S. territories; (3) providers with listed specialties that are not licensed to prescribe opioid medications.[5] In addition, provider location is not populated for any prescribers in the CMS Part D PUF from 2010, 2011, or 2012. Therefore, state location for each NPI was obtained from records of the Physician Masterfile, maintained by the American Medical Association (AMA) and purchased through a database licensing agreement.[6] This is necessary to identify whether or not a given provider is practicing in a state where a PDMP was implemented, and the AMA maintains one of the most extensive historical records of health workforce members available. After supplementing the CMS Part D Prescriber PUFs with the

[3] We obtained PUFs from 2013, 2014, 2015, 2016, and 2017 directly from the CMS website. We obtained PUFs from 2010, 2011, and 2012 from ProPublica. Any errors or omissions in the data from ProPublica for 2010-2012 are our own.

[4] 9,451,120 provider-drug-year level observations

[5] These specialties are indicated by a * in Tables B1-B1.

[6] Medical Marketing Service (MMS Inc) is an authorized AMA Database Licensee (DBL) and supplied requested data extracted from the AMA-PPD database for research and statistical analysis.

Table 1: Variable Descriptions

(a) Part D Public Use File Identifiers

Variable Name	Description
NPI	National Provider Identifier for the performing provider on the claim
Drug	Brand name and/or generic name of the drug on the claim
Year	Year in the PUFs begins July 1 of the current year through the cutoff, June 30, of the following year
State	State where the provider is located as reported in National Plan & Provider Enumeration System (NPPES) or the AMA Physician Masterfile
Specialty	(0) Primary Care (1) Dentistry (2) Emergency Medicine (3) Surgery (4) Palliative Care (5) Pain Management (6) Mid-Level Provider (8) Oncology (9) Radiology (10) Specialist (11) Mental Health (12) Addiction Medicine (13) Sports Medicine (14) Physical & Occupational Therapy

(b) Outcome Variables

Variable Name	Description
Prescriptions	Number of prescriptions for a given opioid drug, original and refill, dispensed to Part D beneficiaries by a given provider in a given year
Total Prescriptions	Total aggregated opioid prescriptions per provider per year, original and refill, dispensed to Part D beneficiaries in the PUFs

(c) State-Level Control Variables

Variable Name	Description
Population	Total population (in millions) in the state in which the prescriber practices
Medicare Enrollment	Total number of Medicare beneficiaries (in thousands) in the state
Unemployment Rate	Unemployment rate in the state in which the prescriber practices
Poverty Rate	Poverty rate in the state in which the prescriber practices
Workers' Compensation	Total expenditures for workers compensation (in ten million dollars) in the state in which the prescriber practices

AMA data, we also exclude providers for whom state of practice is still unavailable. Therefore, our sample contains more physicians compared to other prescribing providers, such as physician assistants and nurse practitioners. Finally, we exclude providers who practice in a state that implemented a MA-PDMP prior to 2011. After implementing all of the above exclusionary criteria, the final sample for this analysis contains 631,727 providers (91 percent of observed providers).[7] Identification attributes for this data are described in Table 1a. Our final analytic dataset contains data on opioid prescribing at the provider-drug-year level.

[7] 8,491,401 provider-drug-year level observations (90 percent of observed provider-drug combinations). We are able to cluster standard errors at the provider level for 575,036 providers observed in the data more than once (83 percent of providers in the original PUFs).

3.3 Outcomes

The primary outcome in our analysis is the number of prescriptions for a given opioid drug, original and refill, dispensed to Medicare Part D beneficiaries by a given provider in a given year. We classify a drug in the CMS Part D Prescriber PUF as an opioid if it has a brand and/or generic name corresponding with those listed in Tables B2-B2 in the Appendix. The unit of observation in our data is at the provider-drug-year level. For example, a surgical provider in Georgia in our dataset wrote 244 prescriptions in 2017, original and refill, for the drug "hydrocodone/acetaminophen." In our primary specifications, opioid use disorder (OUD) treatment drugs are included in these outcomes to provide a conservative estimate of the impact of MA-PDMPs on opioid prescribing. Specifically, methadone is treated as an opioid pain medication in our sample because of guidance from CMS.[8] It is critical to note that when a prescriber has 10 or fewer prescriptions for a given drug in any given year, the record is excluded from PUFs to protect the privacy of Medicare beneficiaries. These privacy rules result in an unbalanced panel and will dictate the estimation techniques described in what follows. In validity checks, we consider whether missingness or attrition in the data is correlated with treatment or leads to a bias in estimates or in the size of standard errors. Table 1b provides a complete list of outcomes considered across all analyses.

3.4 Control Variables

We use provider specialty as both a control variable in main regressions and an identification variable by which to stratify our sample. Table 1c provides a list of state-level control variables included in our main analyses. We use Medicare enrollment to adjust for the potential opportunity to prescribe an opioid to a Medicare Part D beneficiary. We also use state-level covariates documented in existing literature as being associated with opioid prescribing or opioid overdose hospitalizations and/or death including the unemployment rate [Hollingsworth et al. (2017)], the poverty rate [Ghertner and Groves (2018)], total population [Ghertner and Groves (2018)], and workers' compensation expenditures [Webster et al. (2009)]. However, our findings are robust to the exclusion of these time-varying controls (while still accounting for population size).

[8] Medicare Part D Coverage of Methadone: "According to CMS, Methadone is not a Part D drug when used for treatment of opioid dependence because it cannot be dispensed for this purpose upon a prescription at a retail pharmacy. It must be administered through a private or public Methadone clinic approved by the SAMHSA. State Medicaid Programs may continue to include the costs of methadone in their bundled payment to qualified drug treatment clinics or hospitals that dispense methadone for opioid dependence. Methadone is a Part D drug when indicated for pain. Due to the increased risk of addiction, overdose, and death related to opioid use, some Medicare drug plans have a program in place to help patients use these medications safely. Quantity limits and safety checks are in place to monitor these medications."

3.5 MA-PDMP Implementation

22 states implemented a PDMP with a mandatory query (MA-PDMP) during our period of interest (2010-2017) − Arkansas, Connecticut, Delaware, Georgia, Indiana, Kentucky, Massachusetts, Minnesota, New Hampshire, New Jersey, New Mexico, New York, Ohio, Oklahoma, Pennsylvania, Rhode Island, South Carolina, Tennessee, Utah, Vermont, Virginia, and West Virginia. Providers practicing in these states are part of the **treatment group**. Providers practicing in states without a MA-PDMP are part of the **control group**. This includes voluntary states and states without a PDMP. We omit all providers practicing in Louisiana from all analyses because they implemented a MA-PDMP in 2008, before the study period. We also omit states who implemented during the study period, but for whom we have less than a full year of data post-implementation (Alaska and Arizona). Four states−California, Illinois, Maryland, and Texas−implemented the mandate after the study period in either 2018 or 2019, and so are included in our control group. Table A1 and Figure A2 in the Appendix provide months and years of MA-PDMP implementation.

3.6 Estimation Strategy

To measure the effect of MA-PDMPs on the prescribing behavior of providers, we employ a standard differences-in-differences (DD) estimation and an event-study design to count data models. These econometric methods compare the prescribing behavior of providers practicing in a state where a MA-PDMP is implemented during the panel to the behavior of those practicing in states without a MA-PDMP. Given the count nature of this outcome and the truncation that occurs in our data to protect patient privacy, we apply truncated Poisson models,[9] as it is well documented that results are biased when truncation is ignored [Greene (2011); Greene (2008); Long (1997)]. Applying this estimation strategy to the CMS Part D PUF data will appropriately adjust estimates for CMS privacy regulations. We observe a provider's prescribing behavior, Y_{ijst}, conditional on $Y_{ijst} > 10$ −, the truncation point of the CMS Part D PUFs. Therefore, a provider's prescribing behavior is given by

$$E\Big[Y_{ijst}|Y_{ijst} > 10, \mathbf{W}_{ijst}\Big] = \exp\Big(\mathbf{W}_{ijst}\Big) \tag{1}$$

$$\begin{aligned}\mathbf{W}_{ijst} = \alpha_s + \theta_t + \beta\text{Mandatory}_s + \delta\text{MA-PDMP}_{st} + \mathbf{Specialty}_{it}\boldsymbol{\eta} \\ + \mathbf{X}_{st}\boldsymbol{\phi} + \ln(\text{Medicare Enrollment}_{st})\end{aligned} \tag{2}$$

[9] We focus on Poisson because the model does not suffer from the "incidental parameters" problem and can adequately accommodate fixed effects [Cameron and Trivedi (2005)].

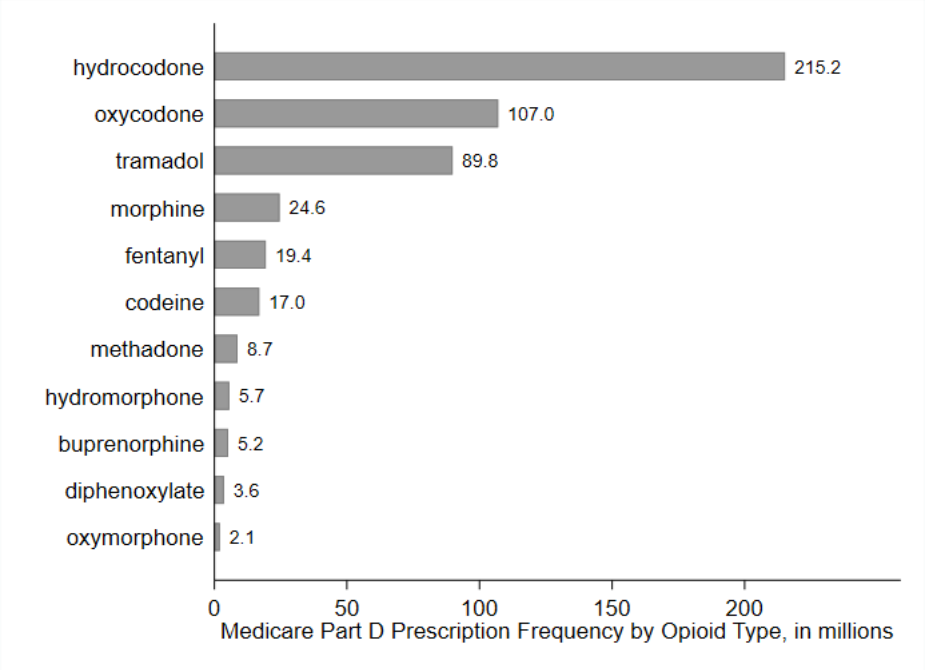
where Y_{ijst} is the number of prescriptions written by prescriber i for opioid j in state s and year t. α_s denotes state fixed effects and θ_t denotes year fixed effects.[10] Mandatory$_s$ is a binary variable denoting whether provider i practices in a state that implements a MA-PDMP during our study period, and MA-PDMP$_{st}$ represents the DD treatment effect. $\mathbf{Specialty}_{it}$ denotes a series of specialty binary variables which controls for different levels of opioid prescribing across specialties as well as other time-invariant, specialty-specific opioid prescribing factors. $\mathbf{X}_{st}$ includes state-level demographic information for state s where the prescriber practices in year t. This includes state-level population, unemployment rates, poverty rates, and expenditures for workers' compensation. Finally, Medicare Enrollment$_{st}$ is the number of total medicare enrollees (standard and Medicare Advantage) in state s and year t. Since Medicare enrollment captures the opportunity to prescribe any drug to a Medicare beneficiary, this measure is used as the exposure, adjusting for the amount of opportunity a provider has to prescribe. In all MA-PDMP specifications, we cluster standard errors at the provider level to minimize issues from having an overpowered sample [Datta and Dave (2017)]. Event study designs use the same specification in equation (1) and (2) but replace the DD treatment effect, MA-PDMP$_{st}$, with time to and time since treatment indicators, MA-PDMP$_{s,t-5}$, MA-PDMP$_{s,t-4}$, ..., MA-PDMP$_{s,t+4}$, MA-PDMP$_{s,t+5}$.

We hypothesize that the mandatory requirement as part of MA-PDMP implementation makes the policy salient, and information from MA-PDMP databases will reduce informational asymmetries in a patient's history of opioid use and potential risk of opioid misuse. However, the a priori effect of improving this informational asymmetry is not clear. A novel component of our approach is allowing the impact of a MA-PDMP implementation to be heterogeneous across provider specialties. It is reasonable to expect differences in information asymmetry across specialty types, given the large variance in the number of opioids prescribed among different types of physicians [Levy et al. (2015) and Ringwalt et al. (2014)]. For instance, Family Medicine physicians and Emergency Medicine physicians not only have different patient populations, disease presentations, and prescribing behaviors (independent of state policies), but also differ in their knowledge of patient histories. Not acknowledging ex ante prescribing differences when analyzing the effects of PDMP characteristics may also play a role in the null results found in some studies [e.g. Yarbrough (2017)]. If doctor shopping is prevalent, then implementation of a MA-PDMP may reduce opioid prescribing. Conversely, if doctor shopping is not prevalent, this increase in information may increase a provider's confidence in prescribing and therefore lead to an increase in opioid prescriptions.

Prescriber-level factors likely play large a role in opioid prescribing. We suspect that controlling for

[10] In some specifications, we exclude state fixed effects for WI and WY to satisfy parallel trends.

Figure 1: Medicare Part D Prescription Frequency for Opioids by Type, in millions



provider specialty accounts for a lot of the variation in opioid prescribing. This analysis could be improved if other potential confounders like provider experience level, medical training, practice setting, and other demographic characteristics were included. Unfortunately, this level of provider-level information is not available in the CMS Part D PUFs, but may be an important area for future research. It is typical in these circumstances to control for unobserved heterogeneity using provider-level fixed effects. These fixed effects control for time-constant differences between providers like prescribing preferences – for example, a tendency to prescribe a 90-day supply instead of a 30-day supply, or a tendency to prescribe pharmaceuticals in general. However, given the over 600,000 providers in the data, it is computationally infeasible to include provider-level fixed effects. Moreover, it is likely not appropriate to use provider fixed effects with the CMS part D PUFs, since we only observe a small portion of the providers both pre- and post-implementation of PDMPs. Using individual-level fixed effects is not appropriate for estimating the impact of the policy when you cannot accurately estimate a within-effect. For this reason, we rely on state-level fixed effects to capture within-state unobserved effects in opioid prescribing. Furthermore, there is no reason to suspect that physician-level unobserved attributes are correlated with the implementation of the policy, or that they would affect the identification of the policies considered in this analysis.

Table 2: Summary Statistics

Opioid Prescribing Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Prescriptions per provider-drug-year	58.89	118.17	11	8,466
Number of distinct drugs prescribed per provider-year	5.5	4.0	1	36
Total opioid prescriptions per provider	438.24	781.31	11	26,391

State Characteristic Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Population (millions)	12.64	10.80	0.56	39.54
Medicare enrollment (in thousands)	2,016.67	1,509.21	64.03	5,915.87
Unemployment rate	6.59	2.11	2.40	12.60
Poverty rate	13.80	2.82	6.40	22.70
Workers' compensation (ten millions)	58.55	70.65	0.79	223.08

3.7 Descriptive and Summary Statistics

Figure 1 graphs the broad opioid types most commonly prescribed and dispensed to Part D beneficiaries in the U.S. in our study sample. Hydrocodone and Oxycodone, two of the top drugs associated with opioid overdose deaths [Ossiander (2014)], are also the two most commonly prescribed opioids in the Medicare population. Hydrocodone comprises 43.04 percent of all claims for opioids (Table A2), followed by Oxycodone (21.41 percent) and Tramadol (17.97 percent). Morphine is the fourth most frequently prescribed opioid in the Medicare population, but not close in magnitude to the first three. Table 2 presents summary statistics for continuous variables in our analysis. These statistics highlight a key issue in opioid prescribing. The mean number of prescriptions for a given opioid per provider per year is about 58.9, but the magnitude of the difference between the highest and lowest is large, ranging from 11 to 8,466 prescriptions per year. This is driven both by differences between providers as well as differences between drugs. Over 36.9 percent of providers in our sample prescribe less than 15 total opioid prescriptions per year. Around 3 percent prescribe more than 1,000 opioid per year in at least one year in our sample. Though a number of these prescribers with high numbers of prescriptions may be inappropriately prescribing, it may also reflect differences across areas of medicine in the tendencies and patterns of opioid prescribing.

To explore these potential differences, Table 3 presents similar opioid prescribing statistics stratified by specialty.[11] It is clear that opioid prescribing varies by specialty. Not surprisingly, providers in pain management prescribe the most opioids on average (Table 3a). We also see that there is a correlation between the

[11] Medical specialty as reported on NPI Part B claims; the specialty code associated with the largest number of claims is reported.

Table 3: Annual Opioid Prescribing Statistics by Specialty

(a) Number of prescriptions per drug per provider

Specialty	Mean	Std Dev	Min	Max
Primary Care	62.7	114.9	11	7096
Dentist	31.8	32.2	11	749
Emergency	36.8	62.2	11	3296
Surgery	61.7	132.8	11	8466
Palliative Care	39.0	52.0	11	1266
Pain Mgmt	125.9	272.7	11	7957
Mid-Level	51.7	95.8	11	7431
Oncology	30.6	36.1	11	2903
Radiology	48.3	113.4	11	1759
Specialist	47.0	93.6	11	6705
Inpatient	62.4	113.5	11	6530
Mental Health	39.9	75.6	11	3814
Addiction	74.6	110.9	11	1673
Sports	84.6	184.9	11	7979
Total	59.2	118.7	11	8466

(b) Number of distinct drugs per provider

Specialty	Mean	Std Dev	Min	Max
Primary Care	6.1	3.3	1.0	32.0
Dentist	1.4	0.7	1.0	8.0
Emergency	2.5	2.1	1.0	30.0
Surgery	4.4	4.2	1.0	29.0
Palliative Care	6.2	2.9	1.0	19.0
Pain Mgt	12.3	4.9	1.0	34.0
Mid-Level	4.9	4.1	1.0	28.0
Oncology	4.7	2.6	1.0	17.0
Radiology	3.8	4.1	1.0	21.0
Specialist	3.9	3.6	1.0	36.0
Inpatient	6.1	3.3	1.0	30.0
Mental Health	3.3	3.3	1.0	30.0
Addiction	7.4	5.4	1.0	20.0
Sports	9.4	5.4	1.0	33.0
Total	5.5	4.0	1.0	36.0

number of prescriptions and the number of distinct drugs prescribed (Table 3b). Pain management providers use a wider array of opioid drugs, 12.3 distinct drugs on average compared to dentists and emergency room providers at 1.4 and 2.5 distinct drugs on average, respectively. Interestingly, primary care providers prescribe the fourth most opioids on average, while oncology providers prescribe the least. Given the vast heterogeneity in prescribing, it seems that estimating specialty-specific effects in response to MA-PDMPs is appropriate. This confirms our approach of stratification by specialty.

4 Results

4.1 Validity

Before estimating the impact of MA-PDMPs on opioid prescribing, we conduct a number of validity checks and present that evidence here. A key identifying assumption for our model is that MA-PDMP states be similar to non-MA-PDMP states prior to implementation of the MA-PDMP (i.e. "parallel trends" assumption). We provide evidence to support this assumption using an event study design, depicted in Figure 2. We present event studies with 95 percent confidence intervals for both the full sample and event studies stratified by specialty. The figures provide the estimated coefficients and 95 percent confidence intervals from equation (2). The vast majority of sub-sample specifications do not provide evidence of a violation of the parallel trends assumption. This coincides with that of Buchmueller and Carey (2018),

where the parallel trends assumption is not violated when analyzing opioid misuse and doctor shopping among Medicare Part D beneficiaries. Similarly, Dave et al. (2017) find evidence to suggest that adoption of the mandatory query provision is exogenous in the sample of states with an operational PDMP when examining opioid treatment admissions into substance abuse facilities.

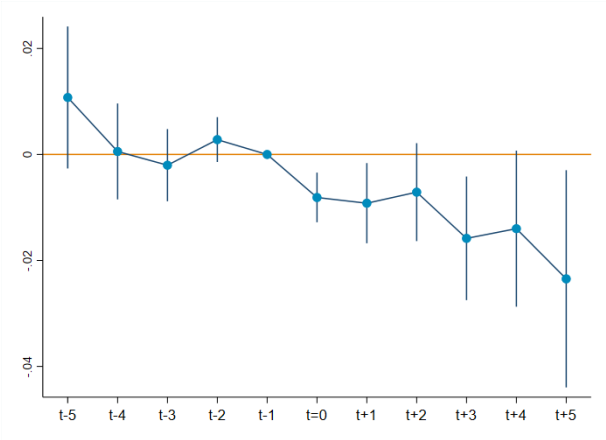
We observe an overall reduction in opioid prescribing in the full sample in most post-implementation years. This decrease is driven by primary care (Figure 2b) and inpatient care providers (Figure 2l). For both types of providers, the largest decrease in prescribing occurs the first couple of years after their state of residence adopts a MA-PDMP. Although they continue to prescribe fewer opioids compared to non MA-PDMP providers, the reductions level off. Note that the confidence intervals for these later post-implementation years widen due to a loss of precision because fewer states and providers are used to estimate effects five years after MA-PDMP implementation. We also observe a decrease in prescribing for emergency medicine providers; however, the effects are very imprecisely estimated. Most interestingly, we see an increase in prescribing for palliative care and oncology providers. Palliative care providers in MA-PDMP states increase prescribing compared to those in non MA-PDMP states in all post-implementation years. Conversely, the oncology increase seems to be transitory, with statistically significant increases two to four years after MA-PDMP adoption that become widely imprecise five years after implementation. There are two specialties with violations of the parallel trends assumption: mid-level providers and mental health providers, which are discussed in more detail below.

4.1.1 Mid-Level and Mental Health Providers

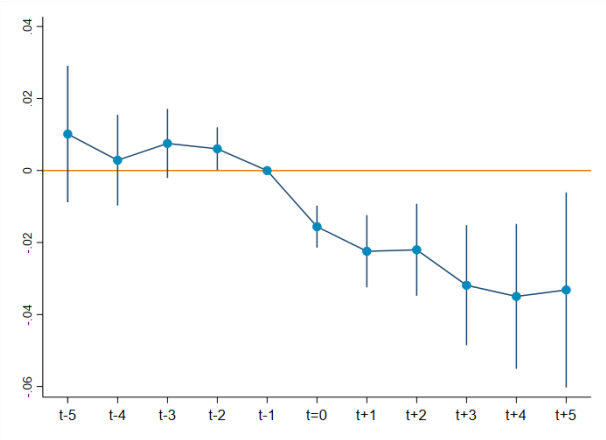
Note that we adjust the event study for mid-level providers due to the way they are observed in our data structure. Mid-level includes non-physician healthcare providers with the authority to prescribe controlled substances, which varies by state. Some examples of mid-level providers are nurse practitioners, nurse anesthetists, and physician assistants. As a reminder, since a provider's state of residence was not provided by CMS in 2010-2012, we supplemented the state variable for those years with an NPI match on AMA records, which documents provider location for physicians but not for other prescribing providers like mid-levels. The estimates for pre-implementation years that include 2010, 2011, or 2012 are estimated using only 20 mid-level providers total, for whom only 7 practice in a MA-PDMP state. Therefore, the mid-level data samples in 2010, 2011, and 2012 are incomplete. However, when we adjust the study sample to exclude providers in states that implement MA-PDMPs prior to 2013, the evidence of parallel trends violations remains (Figure 2h).

Figure 2: Parallel Trends: MA-PDMP Implementation

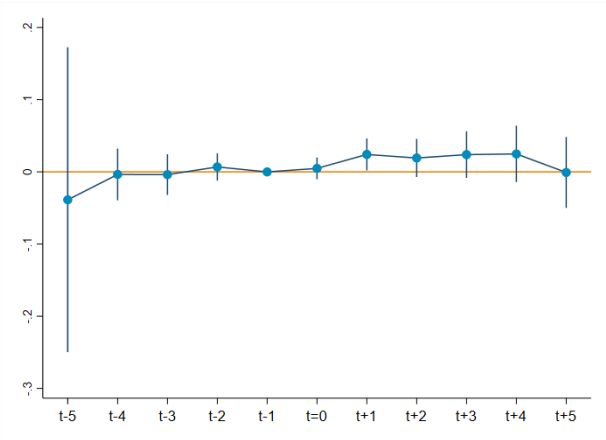
Note. The y-axis plots coefficient estimates and 95 percent confidence intervals from equation (2).



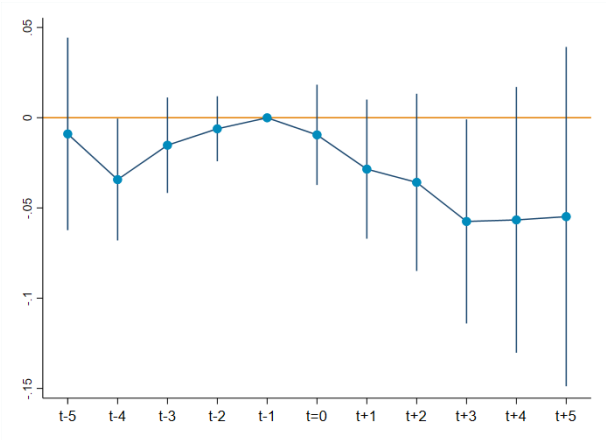
(a) All providers



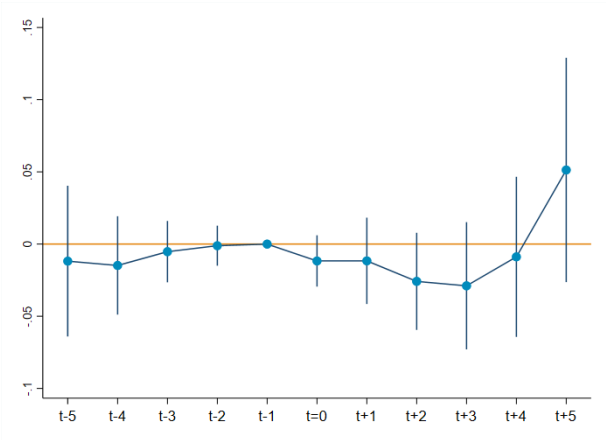
(b) Primary Care



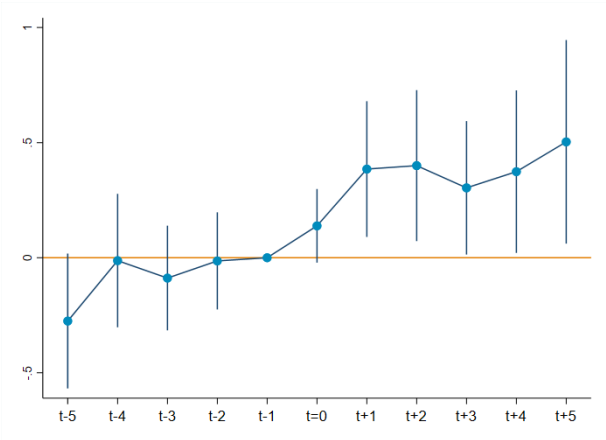
(c) Dentist



(d) Emergency Medicine



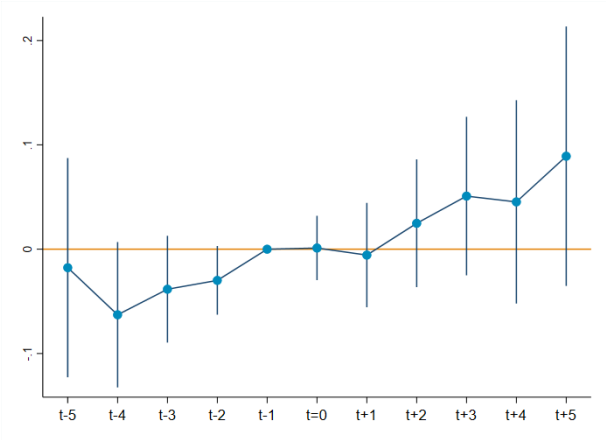
(e) Surgery



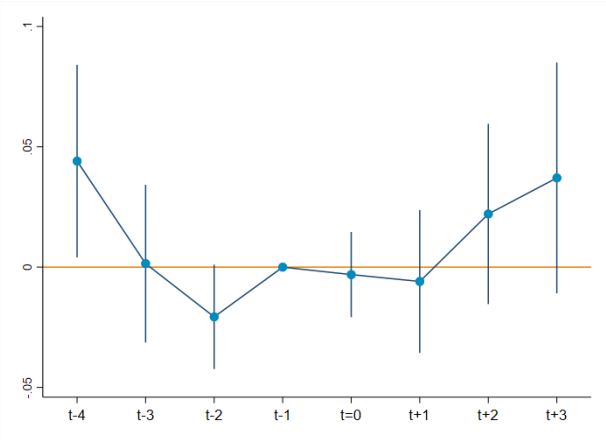
(f) Palliative Care

Figure 2: Parallel Trends: MA-PDMP Implementation, continued

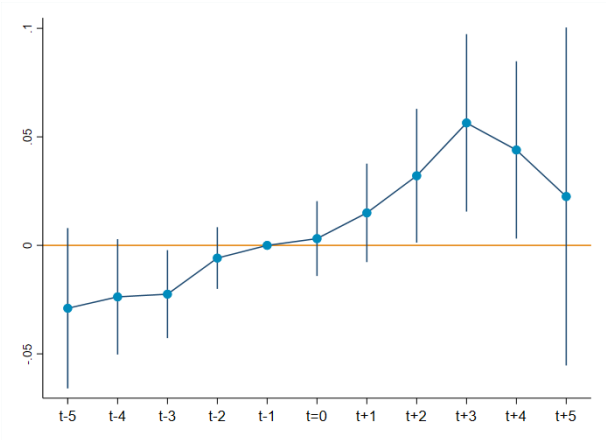
Note. The y-axis plots coefficient estimates and 95 percent confidence intervals from equation (2).



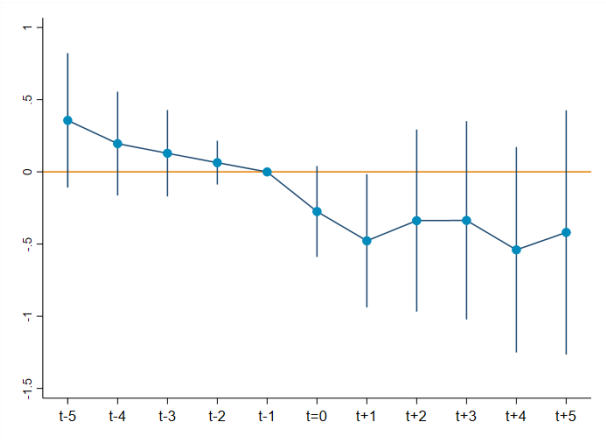
(g) Pain Management



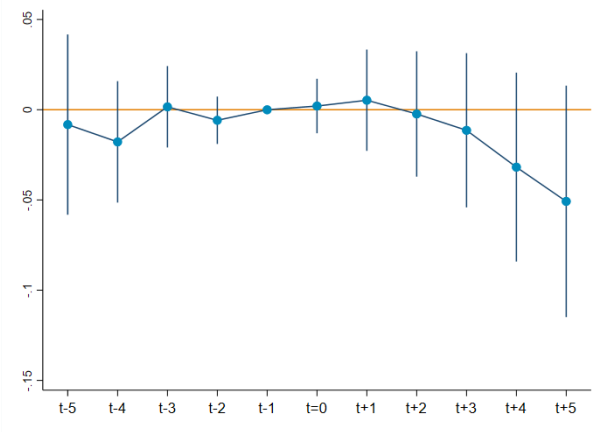
(h) Mid-Level Providers



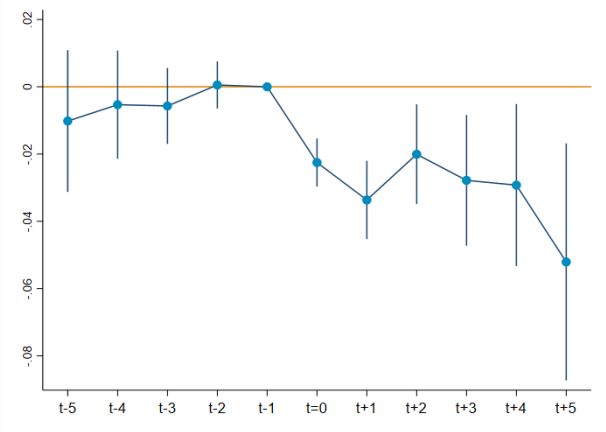
(i) Oncology



(j) Radiology



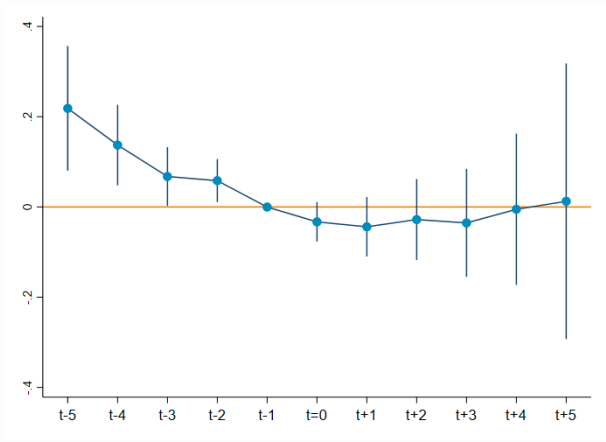
(k) Specialist



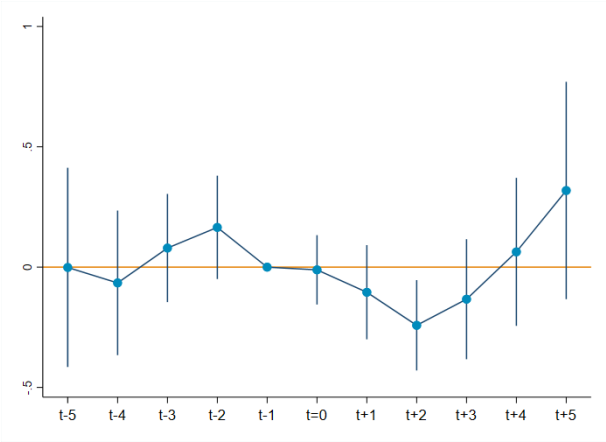
(l) Inpatient Medicine

Figure 2: Parallel Trends: MA-PDMP Implementation, continued

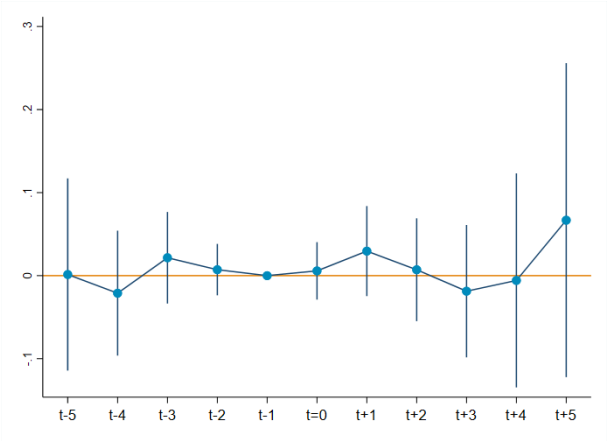
Note. The y-axis plots coefficient estimates and 95 percent confidence intervals from equation (2).



(m) Mental Health



(n) Addiction Medicine



(o) Sports Medicine and Physical Therapy

Mental health providers are observed in the data like most other specialties, but we still observe parallel trend violations. We suspect that this violation is related to the large share of OUD treatment drugs prescribed by mental health providers. We discuss the exclusion of these treatment drugs for all providers and provide a more detailed discussion of mental health providers in section 5. Therefore, in the main results that follow, we do not provide results or conclusions for the impact of MA-PDMPs on mid-level or mental health providers due to violations of a critical model assumption for identification.

4.1.2 Strict Exogeneity and Stability of Treatment

The second key identifying assumption is strict exogeneity, which may be violated if providers adjust opioid prescribing based on the enactment of PDMP regulations prior to implementation. However, the effect modeled here is a prescriber's access of the program, since we use the year in which prescribers are able to query and access information from the prescription drug database. Therefore, our models are not likely to suffer from anticipation, and strict exogeneity is likely to hold. Another key identification assumption of the DD technique requires that there are no spill-over effects from treated to control providers. In their first decade of implementation, most states did not allow inter-state sharing of prescription drug records or database query access, so only providers in treated states would be exposed to the MA-PDMPs. Finally, for the DD approach to be identified there must be stability in the composition of treatment and control groups. Our panel is considerably unbalanced due to truncation, so we will later evaluate whether our results are robust to the inclusion of only the sample of providers observed longitudinally.

4.1.3 Measurement Error due to Truncation

Another key concern in our approach and in the use of CMS Part D PUFs is that the truncation that occurs for beneficiary privacy in the PUFs may be correlated with the implementation of MA-PDMPs. Doctors who change prescribing along the extensive or intensive margin close to the truncation point may move in or out of the CMS PUFs because of treatment. If this is the case, the measurement error due to truncation will be correlated with MA-PDMP treatment and bias our estimate of the impact of a mandatory query. To assess this issue, we construct a balanced dataset of all providers who appear in the CMS Part D PUFs in any year between 2010 and 2017. We model the probability that a given provider is unobserved in each year in the PUFs as

$$y_{ist} = \begin{cases} 0, & \text{if provider } i \text{ in state } s \text{ is observed in PUFs in year } t \\ 1, & \text{if provider } i \text{ in state } s \text{ is unobserved in PUFs in year } t \end{cases} \tag{3}$$

$$y_{ist} = \alpha_s + \theta_t + \beta \text{Mandatory}_s + \delta \text{MA-PDMP}_{st} + \mathbf{Specialty}_{it}\boldsymbol{\eta} + \mathbf{X}_{st}\boldsymbol{\phi} + \epsilon_{it} \tag{4}$$

We use linear probability models to assess whether the unobserved status is correlated with the implementation of a MA-PDMP. We present these results in Table 4. Overall, MA-PDMP implementation is not associated with the observation status in full sample regressions. We also find that MA-PDMP implementation is not associated with the observation status of prescribers in any specialty. Given this finding, we presume that any missing information for providers occurs at random, which will yield unbiased estimates but may still bias the calculation of standard errors. Thus, we also consider an alternate specification where

Table 4: Correlation between Unobserved Status and MA-PDMP Treatment

Dependent Variable: Binary equal to one if provider is unobserved in a given year in PUFs

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
MA-PDMP$_{st}$	0.010	-0.003	0.019	-0.009	0.026	-0.020
	(0.006)	(0.014)	(0.018)	(0.013)	(0.043)	(0.012)
N	810,544	403,444	317,634	507,661	3,831	28,833

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
MA-PDMP$_{st}$	-0.007	-0.022	0.009	0.005	0.007	-0.010
	(0.015)	(0.035)	(0.010)	(0.006)	(0.064)	(0.012)
N	102,557	8,382	554,405	689,490	1,729	58,310

Note. The specialty sub-sample is provided in the column heading. The treatment group in in each sub-sample analysis include providers in states that implemented a MA-PDMP during the panel. The control group includes providers in states without a MA-PDMP. The estimation technique employed in all specifications is the linear probability model. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

we restrict our analysis to providers who we can observe throughout the entire sample period. These results are presented in Table 7 and discussed further in the Robustness section.

4.2 Main Results

4.2.1 The impact of MA-PDMPs on opioid prescribing

Table 5 presents results for all providers in our sample using the primary specification in equation (1) and (2), where MA-PDMP$_{st}$ is the treatment effect of the MA-PDMP. The first two columns use provider-drug-year level observations, while the second two columns aggregate prescribing at the provider-year-level, which is commonly done with CMS Part D PUFs. Columns 1 and 3 provide incidence rate ratio (IRR) estimates from truncated Poisson regressions, while Columns 2 and 4 provide IRR estimates from Poisson regressions without adjusting for truncation. As depicted in event study designs for the full sample in Figure 2a, results in Table 5 indicate that providers in states with MA-PDMPs decrease the number of prescriptions per drug per provider per year by .08 percent. Using the estimate from column (1) and average prescribing rates provided in Table 2, this is a decrease of only about 2.62 fewer opioid prescriptions per provider per year.[12] This result is robust to alternate specifications provided in Columns (2)-(4), but these specifications do not satisfy parallel trends. Note that the aggregated specifications we estimated tend to overestimate the

[12] $(\beta - 1) * AvgNumberofPrescriptions * AvgNumberofDrugs = (.992 - 1) * 59.62 * 5.5 = 2.62$
The average number of prescriptions and the average number of drugs for each specialty and for the whole sample can be found in Table 3.

Table 5: The Effect of MA-PDMP Implementation on Opioid Prescribing

Dependent Variable:	Y_{ijst}		Y_{ist}	
	(1) Truncated Poisson	(2) Poisson	(3) Truncated Poisson	(4) Poisson
	IRR	IRR	IRR	IRR
Mandatory$_s$	2.836***	2.742***	3.329***	3.319***
	(0.095)	(0.091)	(0.146)	(0.145)
MA-PDMP$_{st}$	0.992**	0.989***	0.982***	0.981***
	(0.004)	(0.004)	(0.005)	(0.005)
State and Year FE	Yes	Yes	Yes	Yes
Opioid-Type FE	Yes	Yes	No	No
N	8,157,891	8,157,891	2,710,557	2,710,557
Wald χ^2	$341,818^{***}$	$358,241^{***}$	$220,214^{***}$	$220,449^{***}$

Note. Y_{ijst} denotes the annual number of prescriptions per drug per provider. Y_{ist} denotes the annual number of total prescriptions per provider. The estimation technique employed is given in the column heading. All specifications included specialty indicators, population, the unemployment rate, worker's compensation, and the poverty rate. Standard errors are given in parentheses and clustered at the provider level. Total medicare enrollment is used as the exposure, and all reported estimates are relative risk ratios. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

effect of MA-PDMPs on opioid prescribing. Table A3 in the Appendix provides full event study regression results for these specifications. Therefore, in what follows, we use the specification in Column (1) for all regressions. Consistent with the previous literature, our full sample results are able to replicate findings found broadly in the literature; MA-PDMPs reduce the supply of prescription opioids [Buchmueller et al. (2019) and Yarbrough (2017)]. However, as previously discussed this number may under- or overestimate the effects for providers in particular specialties. Therefore, we conduct sub-sample analysis by different groups of providers to tease out potential prescribing differences that may exist in response to PDMP implementation or identify potential unintended consequences of the policy.

4.2.2 Differential Effects on Opioid Prescribing by Specialty

Providers in certain areas of medicine may respond in quantitatively and qualitatively different ways to the implementation of a MA-PDMP. For example, information from a query may be less illuminating for providers in areas with more continuity of care or pre-existing knowledge of a majority of their patients. Therefore, conducting a sub-sample analysis stratified by provider type may reveal prescribing differences in response to MA-PDMP implementation or prescribing changes that are too restrictive for certain patient populations. We estimate the effect of MA-PDMPs on the number of prescriptions for each opioid drug, stratified by specialty. IRR estimates from this specification are presented in Table 6. The difference in

Table 6: Differential Effects of MA-PDMPs on Opioid Prescribing by Provider Specialty

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
MA-PDMP$_{st}$	0.977***	1.011	0.984	0.983	1.263***	1.025
	(0.005)	(0.009)	(0.017)	(0.013)	(0.113)	(0.023)
N	2,461,273	184,376	387,956	818,277	9,018	220,318

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
MA-PDMP$_{st}$	1.024**	0.679	1.006	0.977***	0.821**	1.003
	(0.012)	(0.160)	(0.013)	(0.006)	(0.079)	(0.026)
N	219,770	5,217	658,597	1,918,301	3,718	225,423

Note. The specialty sub-sample is provided in the column heading. The treatment group in each sub-sample analysis includes providers in states that implemented a MA-PDMP during the panel. The control group includes providers in states without a MA-PDMP. The estimation technique employed in all specifications is truncated Poisson, and all estimates are provided as IRRs. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

magnitude and significance across specialty supports the stratification of providers. The sub-sample analysis reveals important differential effects that are consistent with event-study figures (Figure 2a): The majority of providers do not significantly change their opioid prescribing in response to MA-PDMPs. The lack of changes among surgical, emergency medicine, and pain management providers makes an important statement about potential unintended side effects of the policy. Providers who treat patients with potentially high levels of pain, few drug substitutes, and an urgency for treatment for pain do not change their prescribing behavior after implementation of the MA-PDMP.

The policy effects we observe demonstrate broader changes in opioid prescribing due to MA-PDMPs than just aiding providers in detecting doctor-shopping. Among those who do change prescribing, there are differential effects between high continuity of care and low continuity of care settings. We find a decrease in prescribing for family medicine and inpatient providers; the 2.3 percent decrease is roughly 9 fewer opioids prescribed annually for both Family Medicine and Inpatient providers. These are both specialties with declining provider continuity of care in the U.S. healthcare system [van Walraven et al. (2010); Haggerty et al. (2003)], where opioid history information asymmetries between patients and providers may be prevalent. The decrease for these providers may also be due in part to the typically wide spectrum of patients they see. The array of patient presentations may result in less specialized knowledge related to opioids and pain medication options [Singh and Pushkin (2019)]. Therefore, ex ante policy implementation, both primary care and inpatient providers may have more readily prescribed opioids for pain. Previous work finds that primary care physicians underutilize urine toxicology tests before prescribing opioids except when a system

to track patients with a previous opioid history is available [Bhamb et al. (2006)]. The largest decrease we see is for addiction providers, who prescribe 17.9 percent fewer opioids during post-treatment years. Given the average volume of prescriptions among these providers, they prescribe about 99 fewer opioids annually on average as a result of a MA-PDMP. However, when OUD treatment drugs are excluded in a later robustness check, this effect is no longer statistically significant. There are also a much smaller number of providers in our data for addiction medicine (about 323 providers), so the power to detect differences for these providers is not as large as the power for primary care and inpatient medicine providers.

Interestingly, we also find increases in opioid prescribing among some providers. Both oncology and palliative care providers increase opioid prescribing in response to MA-PDMPs. Oncology providers increase prescribing by 2.4 percent, which is roughly 3.45 more opioid scripts per year. Palliative care providers prescribe about 63.5 more opioids post MA-PDMP implementation. These results may indicate that these providers are more comfortable prescribing after checking a PDMP. Oncology and palliative care providers are relatively most disposed to prescribe opioids for painful treatments and end of life care. Being mandated to query PDMPs may give them an ability to reduce liability. This result is particularly of interest given the recent concern surrounding the access to opioids for patients in the most need of treatments involving controlled substances [Dalal and Bruera (2019), Yuanhong Lai et al. (2019), and Allen et al. (2020)]. Our findings suggests the quality of life of these patients may be impacted by MA-PDMPS in multiple ways. Opioids may improve the quality of end of life care, particularly when patients are living longer with terminal illnesses like cancer [Pinkerton et al. (2020)]. Conversely, we must also acknowledge that longer life spans with chronic pain can increase the probability for misuse and OUD. There may be concerns that opioids are not effective at treating chronic pain, given little evidence of such effects [Bemand-Qureshi et al. (2019)]. If the latter is the case, then policymakers may be concerned that MA-PDMPs are leading to higher levels of chronic pain opioid prescribing among oncology and palliative care providers. The effects observed among oncology and palliative care providers may also show that the use of information from a PDMP may serve as liability protection for providers [Haffajee et al. (2015) and Schreiner (2012)].

5 Robustness Checks

We consider a number of robustness checks to bolster the conclusions of our study; these are found in Table 6. For reference, IRR estimates from Table 6 are provided in the first row of each of the robustness check tables in this section, and all results from corresponding robustness checks present IRR estimates.

Table 7: Robustness Checks for Inclusion and Exclusion Criteria

Dependent Variable: Number of prescriptions per provider per drug per year

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
			Original Estimates, Table 6			
MA-PDMP$_{st}$	0.977***	1.011	0.984	0.983	1.263***	1.025
	(0.005)	(0.009)	(0.017)	(0.013)	(0.113)	(0.023)
N	2,461,273	184,376	387,956	818,277	9,018	220,318
			Panel A: Excluding OUD Treatment Drugs			
MA-PDMP$_{st}$	0.976***	1.011	0.972*	0.983	1.274**	1.022
	(0.005)	(0.009)	(0.017)	(0.013)	(0.120)	(0.023)
N	2,353,719	184,324	383,801	799,258	8,075	198,554
			Panel B: Longitudinal Sample Only			
MA-PDMP$_{st}$	0.968***	1.012	0.994	0.981	1.259*	1.014
	(0.005)	(0.049)	(0.021)	(0.013)	(0.175)	(0.024)
N	1,836,684	5,475	230,035	547,511	3,647	168,386
			Panel C: Most Commonly Prescribed Opioids Only			
MA-PDMP$_{st}$	0.976***	1.005	0.971*	0.992	1.332**	1.024
	(0.005)	(0.010)	(0.017)	(0.012)	(0.155)	(0.026)
N	1,676,823	146,060	348,922	678,701	4,219	111,964

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
			Original Estimates, Table 6			
MA-PDMP$_{st}$	1.024**	0.679	1.006	0.977***	0.821**	1.003
	(0.012)	(0.160)	(0.013)	(0.006)	(0.079)	(0.026)
N	219,770	5,217	658,597	1,918,301	3,718	225,423
			Panel D: Excluding OUD Treatment Drugs			
MA-PDMP$_{st}$	1.023*	0.646*	1.005	0.975***	0.722	1.005
	(0.012)	(0.166)	(0.013)	(0.006)	(0.157)	(0.025)
N	215,832	4,885	642,193	1,846,524	1,732	209,731
			Panel E: Longitudinal Sample Only			
MA-PDMP$_{st}$	1.018	0.921	0.982	0.975***	0.866	0.991
	(0.013)	(0.242)	(0.013)	(0.006)	(0.099)	(0.023)
N	145,257	1,594	373,756	1,444,143	2,118	165,970
			Panel F: Most Commonly Prescribed Opioids Only			
MA-PDMP$_{st}$	1.035***	0.610*	1.014	0.978***	0.657	1.011
	(0.014)	(0.173)	(0.014)	(0.006)	(0.195)	(0.029)
N	137,960	4,002	503,173	1,307,920	1,055	137,692

Note. The specialty sub-sample is provided in the column heading. The treatment group in in each sub-sample analysis includes providers in states that implemented MA-PDMPs during the panel. The control group includes providers in states without a MA-PDMP. The estimation technique employed in all specifications is truncated Poisson, and all estimates are provided as IRRs. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To test whether our initial results are robust, we run regressions with the following adjustments to our study exclusion criteria: (1) the exclusion of opioid use disorder drugs (Table 7, Panel A and D), (2) the exclusion of providers who are not observed longitudinally (Table 7, Panel B and E), and (3) the exclusion of uncommonly prescribed opioids (Table 7, Panel C and F). We also assess whether results are robust to the exclusion of providers in early MA-PDMP adoption states (Table 8), as well as to the adjustment for several other important opioid policies including (1) the implementation of prescription limit policies (Table 9), (2) PDMP delegation (Table 10), and (3) pain clinic regulations. Our initial results are robust to each of these additional tests, which are discussed in more detail below.

5.1 Adjusting Inclusion Criteria

First, we consider that medication-assisted treatment for opioid use disorder (OUD) often includes the prescribing of drugs that are still classified as opioids (e.g. buprenorphine, naltrexone, and naloxone). On average, only 2.9 percent of prescriptions in our sample are written for OUD treatment drugs (Table A2). Given that the use of treatment drugs has implications that differ from opioid pain relievers, we test the robustness of our main specification by excluding drugs used in OUD treatment. Results from this analysis are presented in Table 7. Overall, our main results are consistent. We observe a slightly more precise and negative estimate for emergency medicine providers.

Further, we suspect that differences in OUD treatment drug prescribing may drive the violation of parallel trends among mental health providers, where OUD treatment prescriptions comprise 58.8 percent of all opioid prescriptions,[13] as opposed to 2.9 percent among providers in other specialties. To confirm this suspicion, we adjust the event study design to stratify the sample of opioids prescribed by Mental Health providers into an OUD treatment drug sample (Figure A1a) and a non-OUD treatment opioid drug sample (Figure A1b). This confirms that the parallel trends violation is largely driven by the inclusion of OUD treatment drugs. However, the post-treatment effects remain imprecise, thus we do not see a discernible effect on opioid prescribing among mental health providers as a result of the mandate. Future work should consider whether MA-PDMPs may be able to assist providers in identifying opioid use disorders. Medication-assisted treatment is one of the few proven strategies to reduce opioid misuse [Saloner and Barry (2018)] and is not widely prescribed by many specialties in our Medicare Part D sample.

Second, a limitation of CMS privacy rules is that we can not observe every provider for the entirety of the sample period. If this data is not missing at random, this may bias our results. In the validity

[13] For instance, buprenorphine (64.9 percent of OUD treatment drugs prescribed), naltrexone (29.5 percent), and methadone and naloxone (5.6 percent).

subsection (above) we show that the measurement error associated with truncation is not associated with the implementation of MA-PDMPs; providers who change prescribing along the extensive margin are not "moving" in or out of our dataset because of a MA-PDMP. We complement this analysis by restricting our main specification to providers we observe in every period of the sample, i.e. creating a balanced panel of longitudinally observed providers. These results are presented in Table 7 panels B and E and are similar to the results we obtain in our main specification in Table 6.

Third, given that some opioids are vastly more popular than others, it is of interest to see if our results are consistent for only the most popular opioids. There is also the 2010 abuse-deterrent reformulation of OxyContin, whose active ingredient is oxycodone (the second most prescribed opioid in our data). This supply-side intervention, which limited access to opioids [Alpert et al. (2018)], may have affected subsequent prescribing of this drug. Thus, we consider a specification that restricts the data to Hydrocodone, Oxycodone, and Tramadol. The results for the top three opioids are presented in Panels C and F in Table 7. Our main findings are robust to this restriction.

Fourth, providers across specialties tend to use different drugs for different patient needs. It may be important to adjust for the type of opioids prescribed. To account for these differences across drugs, we also implement an alternate specification that includes opioid-type fixed effects to account for time-constant preferences for prescribing certain opioids relative to others. Results from this specification are provided in Table A4 in the Appendix and are consistent with our main findings. Finally, we also evaluate the robustness of our results to the omission of state-level covariates. Our findings are robust to the exclusion of state-level time-varying controls while still accounting for population size.

5.2 Time-varying Implementation of MA-PDMPs

We also acknowledge that the time-varying nature of MA-PDMP implementation may generate bias in our estimates, particularly when we include early adopting states [Goodman-Bacon (2018)]. Therefore we consider a specification where we drop the early MA-PDMP adopters (years 2011 and 2012). These results are presented in Table 8. Given the unbalanced provider-drug construction of our data, along with the count nature of our outcome, we do not directly test the weighting issues addressed in [Goodman-Bacon (2018)]. When we drop these states our main results are robust, and for some specialties (palliative, oncology) the magnitude of our estimates is larger.

Table 8: Excluding Early MA-PDMP Adopting States

Dependent Variable: Number of Prescriptions per Provider per Drug per Year

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
			Original Estimates, Table 6			
MA-PDMP$_{st}$	0.977***	1.011	0.984	0.983	1.263***	1.025
	(0.005)	(0.009)	(0.017)	(0.013)	(0.113)	(0.023)
N	2,461,273	184,376	387,956	818,277	9,018	220,318
			Panel A: Excluding states implementing MA-PDMP in 2011			
MA-PDMP$_{st}$	0.978***	1.010	0.985	0.988	1.263***	1.025
	(0.005)	(0.009)	(0.018)	(0.013)	(0.113)	(0.024)
N	2,414,226	180,628	381,602	805,248	9,017	217,285
			Panel B: Excluding states implementing MA-PDMP in 2011 and 2012			
MA-PDMP$_{st}$	0.977***	1.006	0.999	0.984	1.374***	1.024
	(0.005)	(0.009)	(0.020)	(0.015)	(0.148)	(0.028)
N	2,196,332	165,822	346,519	738,298	7,839	198,285

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
			Original Estimates, Table 6			
MA-PDMP$_{st}$	1.024**	0.679	1.006	0.977***	0.821**	1.003
	(0.012)	(0.160)	(0.013)	(0.006)	(0.079)	(0.026)
N	219,770	5,217	658,597	1,918,301	3,718	225,423
			Panel C: Excluding states implementing MA-PDMP in 2011			
MA-PDMP$_{st}$	1.023**	0.693	1.005	0.977***	0.832*	1.008
	(0.012)	(0.166)	(0.013)	(0.006)	(0.080)	(0.026)
N	216,542	5,069	650,448	1,900,391	3,636	222,917
			Panel D: Excluding states implementing MA-PDMP in 2011 and 2012			
MA-PDMP$_{st}$	1.037***	0.680	1.007	0.979***	0.833*	1.010
	(0.013)	(0.169)	(0.015)	(0.006)	(0.082)	(0.029)
N	197,262	4,752	605,158	1,761,679	3,401	206,578

Note. The specialty sub-sample is provided in the column heading. The treatment group in each sub-sample analysis includes providers in states that implemented a MA-PDMP during the panel. The control group includes providers in states without a MA-PDMP. The estimation technique employed in all specifications is truncated Poisson, and all estimates are provided as IRRs. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Adjusting for Other Opioid Prescribing Policies

Another potential concern is that our identification strategy relies on the assumption that states with different PDMP policies do not differ based on unobservables that change over time, which may also affect opioid prescribing. Specifically, it is important to consider whether our results are picking up other concurrent

opioid-related policies. Given the debilitating effects of the epidemic, some states adopted additional policies around the same time that MA-PDMPs were instituted. The Prescription Drug Abuse Policy System has tracked a variety of key state laws related to prescription drug abuse.[14] During our study period, several potentially confounding policies were implemented: (1) limits on initial prescription length, (2) the potential moderation of MA-PDMPs due to access delegation policies, and (3) pain clinic laws. Limits on the length of initial prescriptions likely have the most salient effect on all providers in our sample, as they have been found to reduce the average length of an initial prescription but increase the frequency of prescriptions [Sacks et al. (2019)].

5.3.1 Prescription Limit Laws

We first consider whether MA-PDMP estimates are driven by additional prescribing restrictions by adjusting for whether a state has implemented limits on initial prescription lengths. The vast majority of states in the treatment group implemented this policy either in 2016 or 2017 (described in Figure A2 and Table A5). We present IRR estimates for these specifications in Table 9. Overall our results are similar to our main findings. We see that primary care reductions in prescribing are driven by both the mandate and prescribing limits. We also see an increase in the number of prescriptions by dentists and oncologists residing in states with prescribing limits. This finding is not surprising given the finding by [Sacks et al. (2019)] that prescribing limits increase the number of short-term prescriptions.

5.3.2 Does Delegating PDMP search to Others Dampen the Effects of MA-PDMPs?

Some states allow prescribing providers to delegate the task of querying the PDMP to other health professionals. Thus, PDMP delegate legislation may also affect the saliency of information from MA-PDMPs that influences prescribing. As proposed by Buchmueller and Carey (2018), we test the sensitivity of our results by segmenting MA-PDMPs into two groups, those that allow the delegation of access and those that do not. We implement this potential moderation on the effect of MA-PDMPs by interacting MA-PDMP$_{st}$ with a post-implementation binary for delegation, Delegate Access$_{st}$. We then include both treatment effects, MA-PDMP$_{st}$ and MA-PDMP$_{st}$*Delegate Access$_{st}$, in the same regression. MA-PDMP$_{st}$ provides the impact of MA-PDMPs on opioid prescribing when prescribing providers are not permitted to delegate the task; MA-PDMP$_{st}$*Delegate Access$_{st}$ provides the impact of MA-PDMPs on opioid prescribing among providers who are permitted to delegate the task to someone else. Overall, the results in Table 10 suggest that the

[14] More information can be found at http://www.pdaps.org/.

Table 9: MA-PDMP Effect after Adjusting for Initial Prescription Length Laws

Dependent Variable: Number of Prescriptions per Provider per Drug per Year

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
			Original Estimates, Table 6			
MA-PDMP$_{st}$	0.977***	1.011	0.984	0.983	1.263***	1.025
	(0.005)	(0.009)	(0.017)	(0.013)	(0.113)	(0.023)
			Panel A: Adjusted for Prescription Limit Policy Implementation			
MA-PDMP$_{st}$	0.984***	1.006	0.981	0.987	1.263**	1.024
	(0.005)	(0.009)	(0.017)	(0.013)	(0.122)	(0.023)
RX Limit$_{st}$	0.973***	1.024***	1.016	0.982	1.002	1.005
	(0.005)	(0.009)	(0.020)	(0.013)	(0.082)	(0.025)
N	2,461,273	184,376	387,956	818,277	9,018	220,318

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
			Original Estimates, Table 6			
MA-PDMP$_{st}$	1.024**	0.679	1.006	0.977***	0.821**	1.003
	(0.012)	(0.160)	(0.013)	(0.006)	(0.079)	(0.026)
			Panel B: Adjusted for Prescription Limit Policy Implementation			
MA-PDMP$_{st}$	1.018*	0.750	1.010	0.978***	0.849	1.005
	(0.011)	(0.166)	(0.012)	(0.006)	(0.085)	(0.026)
RX Limit$_{st}$	1.029**	0.657*	0.984	0.994	0.912	0.991
	(0.014)	(0.154)	(0.013)	(0.006)	(0.091)	(0.026)
N	219,770	5,217	658,597	1,918,301	3,718	225,423

Note. The specialty sub-sample is provided in the column heading. The treatment group in each sub-sample analysis includes providers in states that implemented a MA-PDMP during the panel. The control group includes providers in states without a MA-PDMP. The estimation technique employed in all specifications is truncated Poisson, and all estimates are provided as IRRs. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

observed impact of MA-PDMPs on opioid prescribing in all of our specifications are driven by providers who are not permitted to delegate the task of PDMP query to others. Significant effects tend to persist, except for palliative care and addiction, where we have smaller sample sizes that may not be powered to estimate these effects with precision. This potential moderating effect of MA-PDMPs has not been well studied, but may suggest that the saliency of this policy is only present when prescribing providers are both mandated to query the PDMP database and cannot delegate that task to someone else.

5.3.3 Pain Management and Pain Clinic Laws

One state in our study sample – West Virginia – implemented a pain clinic law during our sample that requires providers to adhere to prescription limitations [Center for Public Health Law Research (2017)].

Table 10: MA-PDMP Effect After Adjusting for PDMP Delegation

Dependent Variable: Number of Prescriptions per Provider per Drug per Year

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
Original Estimates, Table 6						
MA-PDMP$_{st}$	0.977***	1.011	0.984	0.983	1.263***	1.025
	(0.005)	(0.009)	(0.017)	(0.013)	(0.113)	(0.023)
Panel A: MA-PDMP by Delegated Access Policies						
MA-PDMP$_{st}$	0.974***	0.997	0.977	0.983	1.132	1.007
	(0.009)	(0.015)	(0.027)	(0.021)	(0.225)	(0.035)
MA-PDMP$_{st}$*Delegate Access$_{st}$	1.005	1.017	1.011	1.000	1.132	1.027
	(0.009)	(0.016)	(0.031)	(0.023)	(0.258)	(0.038)
Panel B: MA-PDMP by Delegated Access Policies Adjusted for RX Limit Laws						
MA-PDMP$_{st}$	0.977***	0.993	0.976	0.984	1.132	1.007
	(0.009)	(0.015)	(0.027)	(0.021)	(0.225)	(0.035)
MA-PDMP$_{st}$*Delegate Access$_{st}$	1.010	1.016	1.007	1.004	1.132	1.027
	(0.009)	(0.015)	(0.030)	(0.023)	(0.261)	(0.038)
RX Limit$_{st}$	0.972***	1.023**	1.015	0.982	0.998	1.002
	(0.005)	(0.009)	(0.019)	(0.013)	(0.083)	(0.024)
N	2,461,273	184,376	387,956	818,277	9,018	220,318

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
Original Estimates, Table 6						
MA-PDMP$_{st}$	1.024**	0.679	1.006	0.977***	0.821**	1.003
	(0.012)	(0.160)	(0.013)	(0.006)	(0.079)	(0.026)
Panel C: MA-PDMP by Delegated Access Policies						
MA-PDMP$_{st}$	1.050**	0.982	1.017	0.980*	0.855	1.001
	(0.022)	(0.322)	(0.020)	(0.010)	(0.105)	(0.041)
MA-PDMP$_{st}$*Delegate Access$_{st}$	0.965	0.533*	0.986	0.995	0.943	1.003
	(0.023)	(0.182)	(0.021)	(0.011)	(0.133)	(0.042)
Panel D: MA-PDMP by Delegated Access Policies Adjusted for RX Limit Laws						
MA-PDMP$_{st}$	1.048**	1.000	1.018	0.981*	0.860	1.001
	(0.022)	(0.323)	(0.020)	(0.010)	(0.105)	(0.041)
MA-PDMP$_{st}$*Delegate Access$_{st}$	0.958*	0.593*	0.989	0.997	0.981	1.005
	(0.023)	(0.175)	(0.020)	(0.011)	(0.147)	(0.042)
RX Limit$_{st}$	1.034**	0.726*	0.985	0.994	0.914	0.990
	(0.014)	(0.136)	(0.013)	(0.006)	(0.097)	(0.025)
N	219,770	5,217	658,597	1,918,301	3,718	225,423

Note. The specialty sub-sample is provided in the column heading. The treatment group in in each sub-sample analysis includes providers in states that implemented a MA-PDMP during the panel. The control group includes providers in states without a MA-PDMP. The estimation technique employed in all specifications is truncated Poisson, and all estimates are provided as IRRs. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Other versions of pain clinic laws require certain certifications, medical personnel, or other procedures to be followed, but WV is the only state in our sample whose pain clinic law explicitly puts limits on the

prescribing of pain management providers [Center for Public Health Law Research (2017)]. The text of the law stipulates that "A pain management clinic physician or pharmacist shall not dispense to any patient more than a seventy-two-hour supply of a controlled substance," (W. Va. Code R. § 69-8-10.4a). This law may directly influence the number of prescriptions by pain management providers in WV because according to evidence found in Sacks et al. (2019), providers may write prescriptions for fewer days of supply, but they may also write more of them. Our previous results are robust to the inclusion of this law's implementation among pain clinic providers; neither MA-PDMPs, prescription limit laws, nor explicit pain clinic prescribing requirements have a significant impact on the number of opioid prescriptions in our sample (results available upon request).

5.4 Additional Specifications

MA-PDMPs may influence prescribing in many ways, so we also explore other measures provided by CMS. We consider days supplied in addition to number of prescriptions because emerging guidelines in the most recent decade recommend both reducing the number of days supplied and not offering refills on opioid prescriptions [Dowell et al. (2016a)]. However, one substantial problem with using days supplied is the provider-drug-level truncation that occurs. When a prescriber writes less than ten prescriptions for a given opioid in any year, both the total number of prescriptions and the number of days supplied are unobserved. It is not possible to discern the truncation level of the number of days supplied from fewer than 10 prescriptions. For instance, a provider may supply 9 scripts in a year to be taken over a 9-day or 18-day period − in either case this information is unobserved and the truncation level is not defined. Thus, models cannot be appropriately adjusted as they are with the primary outcome, the number of prescriptions.

We estimate the effect of MA-PDMPs on the number of days supplied for each opioid drug, stratified by specialty. Results from this specification are presented in Table A8. Note that specialities with reductions in the number of opioid prescriptions in Table 6 have similar reductions in the number of days supplied. The 2.9 percent reduction for primary care providers is roughly 42 days per drug. Inpatient providers see a similar decrease of about 47 days per drug. One exception is the estimate for oncology providers, which has the same sign but a wide confidence interval. Given the limitation discussed previously in the truncation of days supplied, results from Table A8 provide only additional evidence of the more reliably estimated results in Table 6, and thus should be interpreted with caution. Interested readers should keep these features of this data in mind when comparing our estimates to those in previous studies that do not account for truncation or aggregate across the truncation level [e.g., Yarbrough (2017) and Graetz et al. (2020)].

6 Discussion

In an effort to analyze a mitigating factor of the opioid epidemic, this paper estimates the role of MA-PDMPs in altering prescribing behavior and whether or not this policy approach has been too restrictive. Specifically, we relax the assumption of response homogeneity across provider specialty and examine if we observe unintended reductions in opioid prescribing for providers whose patients most need these pain relievers. Our results indicate no systemic reductions in opioid prescribing among specialties where opioids may be most needed for pain (e.g. surgery, emergency medicine, oncology, palliative care, or pain management). We find an overall decrease from states adopting a MA-PDMP. This decrease is driven by primary care and inpatient providers. Conversely, we see that palliative care and oncology providers increase their opioid prescribing once they are required to query a PDMP.

Our results exemplify that the information available to providers will directly impact a prescriber's behavior. In the absence of querying a PDMP, providers likely form clinical opinions on appropriate prescribing using a patient's observable characteristics and/or a perceived risk of opioid misuse. However, it's documented that providers often suffer from overconfidence bias. Several studies show that using clinical instinct in prescribing opioids may not be entirely appropriate [Weiner et al. (2013) and Baehren et al. (2010)], leading to both a lack of opioids prescribed to patients who need them and too many opioids prescribed to patients that do not need them. Previous research finds that emergency medicine providers far overestimate the incidence of drug-seeking behavior, and are only correct about this behavior about 43 percent of the time they suspect it [Weiner et al. (2013)]. Moreover, Baehren et al. (2010) finds that 41 percent of prescribers alter clinical treatment after using information from Ohio's PDMP. 61 percent of these prescribers reduce the amount of opioids they prescribe, while 39 percent increase that amount. Therefore, PDMPs can aid in correcting the overconfidence bias in both directions merely by providing more complete and correct information.

It is also important to note that our results (e.g. the increase in palliative care prescribing) do not necessarily indicate that PDMPs are worsening the opioid epidemic. Recall that the goal of a PDMP is to reduce the prevalence of misuse or abuse through appropriate prescribing as a result of more complete information. Thus, given the current trepidation surrounding the prescribing of opioids, PDMPs that decrease information asymmetries can result in more or less opioids prescribed. Our findings do not contradict the aforementioned findings that PDMPs curb doctor shopping. Taken together with Buchmueller and Carey (2018) and Brady et al. (2014), our results indicate that more stringent PDMPs decrease misuse while allow-

ing providers flexibility in prescribing. Note that if one considers opioids to be a poor remedy for long-term chronic pain, then the fact that MA-PDMPs lead to increased opioid prescriptions in certain specialties may be a cause for concern.

Given that 49 out of the 50 states have paid the initial fixed or start-up cost to set up PDMPs, the additional cost associated with implementing a mandatory query are negligible for state governments. Moreover, the benefits of the mandate have become increasingly clear. MA-PDMPs have been found to reduce doctor shopping [Buchmueller and Carey (2018)], substance use treatment admissions [Grecu et al. (2019)], overlapping opioid prescriptions [Bao et al. (2018)], and overdose deaths [Pardo (2017)]. Bao et al. (2018) also show that MA-PDMPs yield additional benefits when they are incorporated into electronic health records systems. The literature points to the mandate as a helpful tool in combating the opioid epidemic. However, provider resistance to using the system, or the opportunity cost of a provider's time to query the system, may burden providers already stretched thin. This is evidenced by low utilization in voluntary states [Rutkow et al. (2015)]. To make PDMPs more effective, policymakers in non-MA-PDMP states should coordinate with providers to understand the barriers to using this tool. Additional training for providers or a targeted campaign highlighting the benefits of using PDMP information may improve their use. In addition, due to the resolution of information asymmetries, MA-PDMPs may also reduce bias (e.g., racial and ethnic) in opioid prescribing [Green et al. (2003),Anderson et al. (2009)]. Future work should consider whether policies addressing information asymmetries can reduce healthcare disparities.

As one of the first studies to both rigorously investigate prescribing patterns following MA-PDMP implementation and allow different effects by specialty, our results offer policymakers new insight into how providers use the information made available by PDMPs. Our results suggest that moving forward, lawmakers should consider policies that enhance the information available to prescribers, which may depend on provider specialty. In practice, it is likely more critical to provide this information in low continuity of care settings. However, provider response to MA-PDMP implementation is only part of the picture. To get a more holistic view for actionable solutions to the opioid epidemic, there are a number of other important issues to consider. For instance, recent work links economic volatility to a rise in opioid use, overdose deaths, and opioid overdose EM visits [Maclean et al. (2020) and Hollingsworth et al. (2017)]. Future work may also want to consider whether decreases in opioid prescribing lead to the use of alternative substances for pain relief, as well as the effects of this change. For instance, Nicholas and Maclean (2019) finds that state medical marijuana laws lead to lower pain and better self-assessed health among older adults. Although the opioid epidemic is complex, understanding the inception of opioid use and the propensity with which

providers prescribe opioids is essential to combating this national emergency.

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A Appendix

MA-PDMP implementation timing acquired from http://www.pdmpassist.org and http://www.pdaps.org/.

Table A1: MA-PDMP Implementation Month, Year

(a) States A-MO

State	Year Implemented	Month Implemented
AK	2017	7
AL		
AR	2017	1
AZ	2017	10
CA	2018	4
CO		
CT	2015	10
DC		
DE	2012	3
FL		
GA	2014	7
HI		
IA		
ID		
IL	2018	1
IN	2014	7
KS		
KY	2012	7
LA	2008	1
MA	2014	7
MD	2018	7
ME		
MI		
MN	2017	1
MO		

(b) States MS-Z

State	Year Implemented	Month Implemented
MS		
MT		
NC		
ND		
NE		
NH	2016	1
NJ	2015	11
NM	2012	9
NV	2007	10
NY	2013	8
OH	2012	3
OK	2011	3
OR		
PA	2017	1
RI	2016	6
SC	2017	5
SD		
TN	2013	7
TX	2019	9
UT	2017	5
VA	2015	7
VT	2015	5
WA		
WI		
WV	2012	6
WY		

Table A2: Medicare Part D Prescription Frequency for Opioids by Type

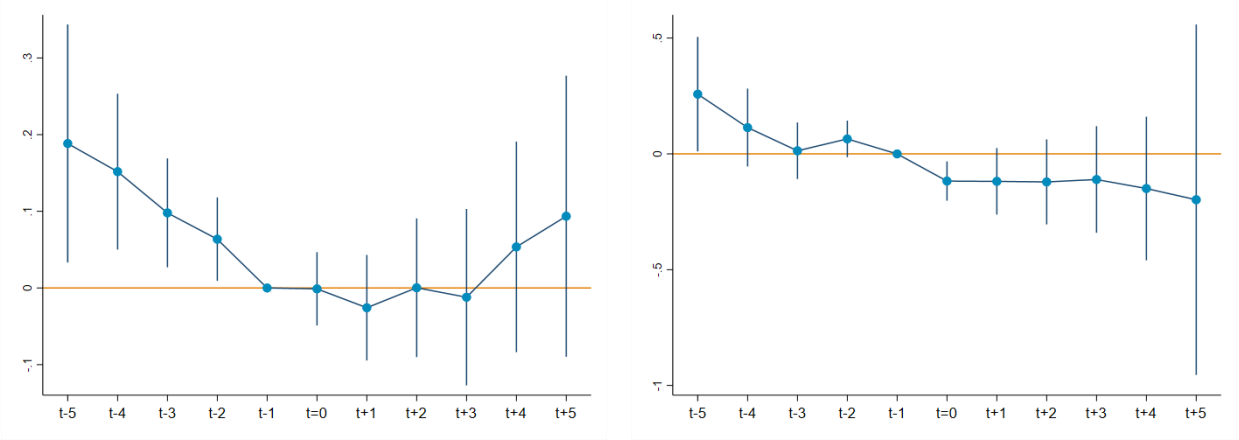
Opioid Type	Frequency	Percent	Cum. Freq.
buprenorphine	5,236,278	1.047	1.047
butorphanol	233,540	0.047	1.094
codeine	16,959,238	3.392	4.485
difenoxin	171	0.000	4.486
dihydrocodeine	9,847	0.002	4.487
diphenoxylate	3,629,414	0.726	5.213
fentanyl	19,418,603	3.883	9.097
hydrocodone	215,197,520	43.036	52.133
hydromorphone	5,680,968	1.136	53.269
levorphanol	16,180	0.003	53.272
meperidine	130,602	0.026	53.298
methadone	8,740,623	1.748	55.046
morphine	24,621,568	4.924	59.970
naloxone	27,714	0.006	59.976
naltrexone	428,410	0.086	60.062
opium	5,851	0.001	60.063
oxycodone	107,037,514	21.406	81.469
oxymorphone	2,115,405	0.423	81.892
pentazocine	53,047	0.011	81.902
pentazocine and naxolone	84,674	0.017	81.919
sufentanil	24	0.000	81.919
tapentadol	566,150	0.113	82.032
tramadol	89,844,843	17.968	100
Total	500,038,184	100	

Table A3: Full Event Study Results for Full Sample

Dependent Variable:	Y_{ijst}		Y_{ist}	
	(1) Truncated Poisson	(2) Poisson	(3) Truncated Poisson	(4) Poisson
	IRR	IRR	IRR	IRR
MA-PDMP Implementation t-5	1.011	1.016**	1.040***	1.040***
	(0.007)	(0.007)	(0.009)	(0.009)
t-4	1.001	1.004	1.009	1.010
	(0.005)	(0.005)	(0.006)	(0.006)
t-3	0.998	1.000	0.999	0.999
	(0.003)	(0.003)	(0.005)	(0.005)
t-2	1.003	1.004*	1.007**	1.007**
	(0.002)	(0.002)	(0.003)	(0.003)
Base-level (t-1)				
t=0	0.992***	0.991***	0.994*	0.994*
	(0.002)	(0.002)	(0.003)	(0.003)
t+1	0.991**	0.989***	0.978***	0.978***
	(0.004)	(0.004)	(0.005)	(0.005)
t+2	0.993	0.990**	0.961***	0.961***
	(0.005)	(0.005)	(0.006)	(0.006)
t+3	0.984***	0.980***	0.942***	0.941***
	(0.006)	(0.006)	(0.007)	(0.007)
t+4	0.986*	0.981***	0.925***	0.924***
	(0.007)	(0.007)	(0.009)	(0.009)
t+5	0.977**	0.971***	0.890***	0.889***
	(0.010)	(0.010)	(0.012)	(0.012)
Mandatory$_s$	2.824***	2.726***	3.289***	3.280***
	(0.097)	(0.092)	(0.146)	(0.145)
Population$_{st}$ (millions)	0.894***	0.886***	0.916***	0.916***
	(0.005)	(0.005)	(0.006)	(0.006)
Unemployment rate$_{st}$	0.985***	0.984***	0.992***	0.992***
	(0.002)	(0.002)	(0.002)	(0.002)
Worker's compensation$_{st}$ (ten millions)				
Poverty rate$_{st}$	1.001	1.000	0.995***	0.995***
	(0.001)	(0.001)	(0.001)	(0.001)
Specialty FE	Yes	Yes	Yes	Yes
State and Year FE	Yes	Yes	Yes	Yes
Opioid-Type FE	Yes	Yes	No	No
Observations	8,157,898	8,157,898	2,710,557	2,710,557
Wald χ^2	$341,818^{***}$	$358,241^{***}$	$220,214^{***}$	$220,449^{***}$

Note. Y_{ijst} denotes the annual number of prescriptions per drug per provider. Y_{ist} denotes the annual number of total prescriptions per provider. The estimation technique employed is given in the column heading. All specifications include a constant. Standard errors are given in parentheses and clustered at the provider level. Total Medicare enrollment is used as the exposure, and all reported estimates are relative risk ratios.
* Statistically significant at the 10 percent level
** Statistically significant at the 5 percent level
*** Statistically significant at the 1 percent level

Figure A1: Parallel Trends: Mental Health Providers and OUD Treatment Drugs



(a) OUD treatment drug sample

(b) Non-OUD treatment opioid drug sample

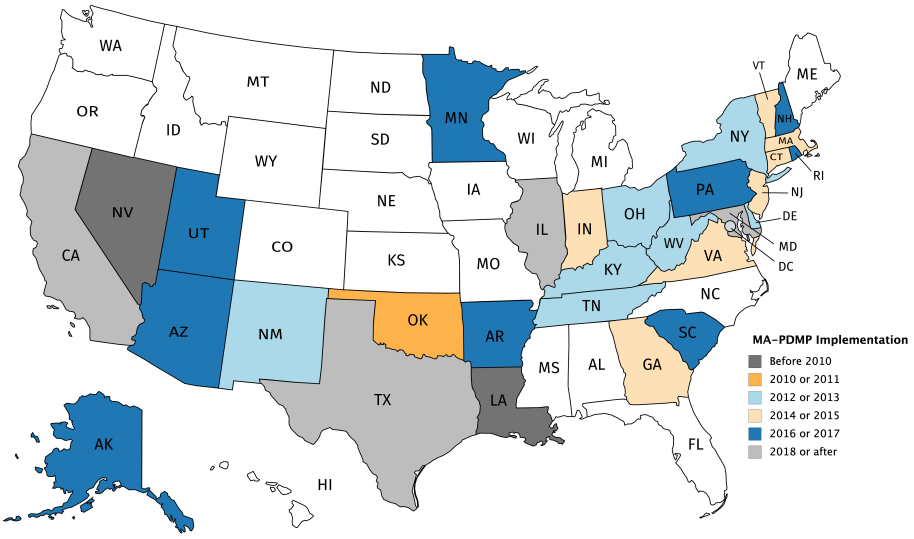
Table A4: Alternate Specification that Includes Opioid Type Fixed Effects

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
Panel A: Original Estimates, Table 6						
MA-PDMP$_{st}$	0.977***	1.011	0.984	0.983	1.263***	1.025
	(0.005)	(0.009)	(0.017)	(0.013)	(0.113)	(0.023)
N	2,461,273	184,376	387,956	818,277	9,018	220,318
Panel B: Estimates with Opioid Type Fixed Effects						
MA-PDMP$_{st}$	0.979***	1.017*	0.986	0.991	1.288***	1.032
	(0.005)	(0.009)	(0.018)	(0.013)	(0.119)	(0.025)
N	2,461,273	184,376	387,956	818,277	9,018	220,318

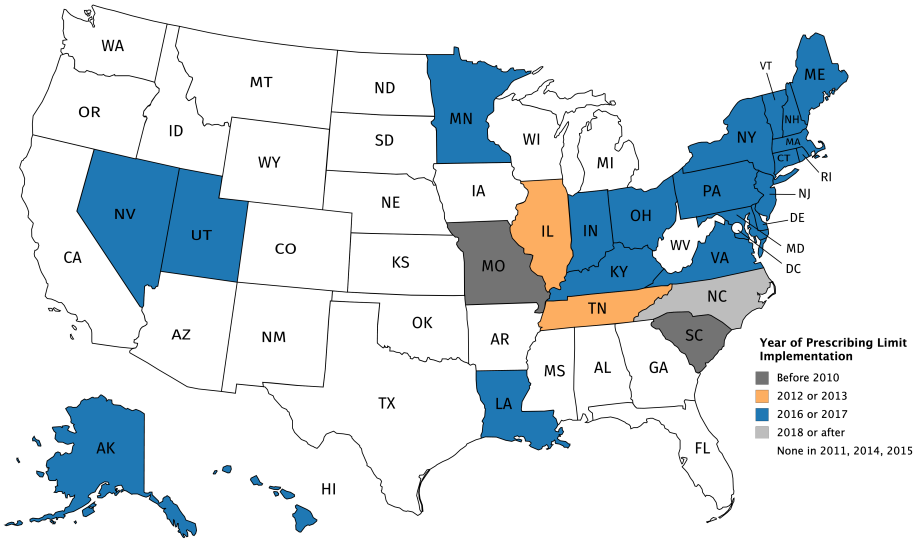
Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
Panel A: Original Estimates, Table 6						
MA-PDMP$_{st}$	1.024**	0.679	1.006	0.977***	0.821**	1.003
	(0.012)	(0.160)	(0.013)	(0.006)	(0.079)	(0.026)
N	219,770	5,217	658,597	1,918,301	3,718	225,423
Panel B: Estimates with Opioid Type Fixed Effects						
MA-PDMP$_{st}$	1.028**	0.655*	1.017	0.986**	0.841*	1.012
	(0.012)	(0.166)	(0.014)	(0.006)	(0.084)	(0.028)
N	219,770	5,217	658,597	1,918,301	3,718	225,423

Note. The specialty sub-sample is provided in the column heading. The treatment group in each sub-sample analysis includes providers in states that implemented an MA-PDMP during the panel. The control group includes providers in states without an MA-PDMP. The estimation technique employed in all specifications is truncated Poisson. All regressions include year fixed effects, state fixed effects, and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Opioid Policy Implementation Maps



(a) MA-PDMP



(b) Prescribing Limits

Table A5: Prescribing Limit Policy Implementation Month, Year

(a) States A-M

State	Year Implemented	Month Implemented	Initial RX Days Limit	Other Limits
AK	2017	7	7	
AL				
AR				
AZ				
CA				
CO				
CT	2016	7	7	
DC				
DE	2017	4	7	
FL				
GA				
HI	2016	7	30	
IA				
ID				
IL	2012	1	20	
IN	2017	7	7	
KS				
KY	2017	6	3	
LA	2017	8	7	
MA	2016	3	7	
MD	2017	5		*a*
ME	2017	1	7	
MI				
MN	2017	7	4	
MO	1988	12	30	

(b) States M-Z

State	Year Implemented	Month Implemented	Initial RX Days Limit	Other Limits
MS				
MT				
NC	2018	1	5	
ND				
NE				
NH	2017	1	7	*a*
NJ	2017	5	5	*a*
NM				
NV	2017	6	14	90 MME/day
NY	2016	7	7	
OH	2017	8	7	30 MME/day
OK				
OR				
PA	2017	1	7	
RI	2017	3	20	30 MME/day
SC	2007	6	31	
SD				
TN	2013	10	30	
TX				
UT	2017	3	7	
VA	2017	3	7	
VT	2017	7	7	*b*
WA				
WI				
WV				
WY				

Note. Information acquired from http://www.pdmpassist.org and http://www.pdaps.org/

a indicates lowest effective dose

b indicates varies by pain level

Table A7: Summary Statistics by Specialty: Days Supplied per Drug (Opioid) per Provider

Specialty	Mean	Std Dev	Min	Max
Primary Care	1452.4	2809.3	11	190920
Dentist	111.5	131.9	11	3696
Emergency	331.2	1495.5	11	98359
Surgery	1039.4	3614.8	11	246559
Palliative	898.6	1170.5	13	23917
Pain Mgmt	3545.5	7788.3	11	216212
Mid-Level	1167.8	2705.0	11	219256
Oncology	606.9	784.6	13	82280
Radiology	1033.0	3226.7	11	51042
Specialist	1056.3	2703.5	11	196130
Inpatient	1460.6	2855.8	11	171469
Mental Health	948.8	1883.7	11	105538
Addiction	1723.9	2650.9	21	42784
Sports	2264.5	5281.9	12	237610
Total	1,314.5	3,151.4	11	246,559

Table A8: Days Supplied per Provider per Drug per Year

Variable	(1) Primary Care	(2) Dentist	(3) Emergency	(4) Surgery	(5) Palliative	(6) Pain
MA-PDMP$_{st}$	0.971***	1.006	1.016	0.964	1.288***	1.020
	(0.005)	(0.013)	(0.053)	(0.022)	(0.118)	(0.023)
N	2,461,273	184,376	387,956	818,277	9,018	220,318

Variable	(7) Oncology	(8) Radiology	(9) Specialist	(10) Inpatient	(11) Addiction	(12) Sports
MA-PDMP$_{st}$	1.023	0.581	1.002	0.968***	0.750***	1.002
	(0.015)	(0.221)	(0.017)	(0.006)	(0.077)	(0.028)
N	219,770	5,217	658,597	1,918,301	3,718	225,423

Note. The specialty sub-sample is provided in the column heading. The treatment group in each sub-sample analysis includes providers in states that implemented an MA-PDMP during the panel. The control group includes providers in states without an MA-PDMP. The estimation technique employed in all specifications is truncated Poisson. All regressions include year fixed effects, state fixed effects, opioid-type fixed effects and state-level covariates. Standard errors are given in parentheses and clustered at the provider level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Data Appendix

Table B1: Specialty Groupings

Specialty	CMS Recorded Specialties Included in Grouping
Primary Care	Family Medicine
	Family Practice
	General Practice
	Geriatric Medicine
	Pediatric Medicine
	Preventive Medicine
	Pediatrics
	Osteopathic Manipulative Medicine
Dentist	Dentist
	Dental Assistant
	Dental Hygienist
	Denturist
	Oral Surgery (Dentists only)
	Oral Surgery (Dentists only)
	Oral Surgery (dentists only)
Emergency Medicine	Emergency Medicine
Surgery	Anesthesiology
	Anesthesiologist Assistants
	Cardiac Surgery
	Colon & Rectal Surgery
	Colorectal Surgery (formerly proctology)
	Colorectal Surgery (Proctology)
	General Surgery
	Hand Surgery
	Maxillofacial Surgery
	Neurosurgery
	Neurological Surgery
	Oral & Maxillofacial Surgery
	Orthopaedic Surgery
	Orthopedic Surgery
	Plastic Surgery
	Plastic and Reconstructive Surgery
	Surgical Oncology
	Surgery
	Thoracic Surgery
	Thoracic Surgery (Cardiothoracic Vascular Surgery)
	Vascular Surgery

Table B1: Specialty Groupings (continued)

Specialty	CMS Recorded Specialties Included in Grouping
Hospice and Palliative Care	Hospice and Palliative Care
Pain Management	Pain Management
	Interventional Pain Management
Mid-Level Provider	Nurse Practitioner
	Physician Assistant
	Certified Clinical Nurse Specialist
	CRNA
	Certified Registered Nurse Anesthetist (CRNA)
Organization*	Health Maintenance Organization
	Preferred Provider Organization
	Clinic/Center
	Multispecialty Clinic/Group Practice
	Ambulance Service Supplier
	Ambulatory Surgical Center
	Assisted Living Facility
	Chronic Disease Hospital
	Clinic or Group Practice
	Exclusive Provider Organization
	General Acute Care Hospital
	Hospital
	Hospital (Dmercs Only)
	Legal Medicine
	Military Hospital
	Military Health Care Provider
	Nursing Facility, Other (Dmercs Only)
	Other Nursing Facility
	Pharmacy
	Point of Service
	Psychiatric Residential Treatment Facility
	Public Health Welfare Agency
	SNF (Dmercs Only)
	Slide Preparation Facility
	Student in an Organized Health Care Education/Training Program
	Substance Abuse Rehabilitation Facility
Oncology	Gynecological/Oncology
	Hematology/Oncology
	Medical Oncology
	Radiation Oncology
	Gynecological Oncology
	Hematology-Oncology
Radiology	Diagnostic Radiology
	Interventional Radiology
	Nuclear Medicine
	Radiology
	Radiologic Technologist

Table B1: Specialty Groupings (continued)

Specialty	CMS Recorded Specialties included in Grouping
Specialists	Allergy/Immunology
	Allergy/ Immunology
	Cardiac Electrophysiology
	Clinical Cardiac Electrophysiology
	Clinical Cardiatric Electrophysiology
	Cardiology
	Cardiovascular Disease (Cardiology)
	Spec/Tech, Cardiovascular
	Dermatology
	Endocrinology
	Gastroenterology
	Hematology
	Infectious Disease
	Medical Genetics
	Medical Genetics, Ph.D. Medical Genetics
	Nephrology
	Neurology
	Obstetrics & Gynecology
	Obstetrics/Gynecology
	Ophthalmology
	Otolaryngology
	Pathology
	Spec/Tech, Pathology
	Independent Medical Examiner
	Peripheral Vascular Disease
	Pulmonary Disease
	Rheumatology
	Sleep Medicine
	Specialist
	Urology
	Optometry
	Podiatry
	Assistant, Podiatric
Inpatient Medicine	Hospitalist
	Internal Medicine
	Interventional Cardiology
	Critical Care (Intensivists)

Table B1: Specialty Groupings (continued)

Specialty	CMS Recorded Specialties included in Grouping
Mental Health	Geriatric Psychiatry
	Neuropsychiatry
	Psychiatry
	Psychiatry & Neurology
	Psychologist (billing independently)
	Clinical Neuropsychologist
	Clinical Psychologist
	Psychologist
	Psychologist, Clinical
	Psychoanalyst
	Behavioral Analyst
	Developmental Therapist
	Marriage & Family Therapist
Addiction Medicine	Addiction Medicine
	Rehabilitation Agency
	Rehabilitation Practitioner
	Rehabilitation Counselor
Sports Medicine	Physical Medicine & Rehabilitation
	Physical Medicine and Rehabilitation
	Sports Medicine
	Neuromusculoskeletal Medicine, Sports M
	Neuromusculoskeletal Medicine, Sports Medicine
Physical or Occupational Therapy	Physical Therapist
	Physical Therapist in Private Practice
	Physical Therapy Assistant
	Occupational Therapy Assistant
	Occupational therapist
Nurse*	Licensed Practical Nurse
	Licensed Vocational Nurse
	Nurse's Aide
	Nursing Care
	Registered Nurse
Pharmacy*	Clinical Pharmacology
	Pharmacist
Alternative Medicine	Acupuncturist
	Naturopath
	Chiropractic
	Homeopath
	Massage Therapist
	Certified Nurse Midwife
	Midwife
Unknown*	Unknown Physician Specialty Code
	Unknown Supplier/Provider
	Undefined Physician type
	Unknown Supplier/Provider Specialty

Table B1: Specialty Groupings (continued)

Specialty	CMS Recorded Specialties Included in Grouping
Non-Prescriber*	Case Manager/Care Coordinator
	Case Manager/Care Coordinator
	Community Health Worker
	Contractor
	Counselor
	Driver
	Genetic Counselor, MS
	Health Educator
	Home Health Aide
	Licensed Clinical Social Worker
	Nutritionist
	Audiologist (billing independently)
	Religious Nonmedical Nursing Personnel
	Respite Care
	Social Worker
	Specialist/Technologist
	Specialist/Technologist, Other
	Speech Language Pathologist
	Technician
	Technician/Technologist
	Optician
	Chore Provider
	Durable Medical Equipment & Medical Supplies
	Day Training, Developmentally Disabled Services
	Emergency Medical Technician, Basic
	Emergency Medical Technician, Intermediate
	Personal Emergency Response Attendant
	Phlebology
	Registered Dietician/Nutrition Professional

Table B2: Drug Names Used to Pull Opioid-Related Prescribing from CMS Part D Prescriber PUF, A-C

Drug (Brand/Generic)	Generic Name	Opioid Type	Opioid Source
ABSTRAL	FENTANYL CITRATE	fentanyl	All three sources
ACETAMIN-CAFF-DIHYDROCODEINE	ACETAMINOPHEN/CAFF/DIHYDROCOD	dihydrocodeine	CMS and CDC
ACETAMINOPH-CAFF-DIHYDROCODEIN	DHCODEINE BT/ACETAMINOPHN/CAFF	dihydrocodeine	All three sources
ACETAMINOPHEN W/CODEINE		codeine	CDC and manual search
ACETAMINOPHEN-CODEINE	ACETAMINOPHEN WITH CODEINE	codeine	All three sources
ACETAMINOPHEN-TRAMADOL		tramadol	Manual search only
ACTIQ	FENTANYL CITRATE	fentanyl	All three sources
APAP-CAFFEINE-DIHYDROCODEINE		dihydrocodeine	Manual search only
ARYMO ER		morphine	CMS only
ASA-BUTALB-CAFFEINE-CODEINE		codeine	CMS only
ASCOMP WITH CODEINE	CODEINE/BUTALBITAL/ASA/CAFFEIN	codeine	CMS and manual search
ASPIRIN-CAFFEINE-DIHYDROCODEIN	DIHYDROCODEINE/ASPIRIN/CAFFEIN	dihydrocodeine	All three sources
ASTRAMORPH-PF		morphine	Manual search only
AVINZA	MORPHINE SULFATE	morphine	All three sources
BELBUCA	BUPRENORPHINE HCL	buprenorphine	CMS and CDC
BELLADONNA-OPIUM	OPIUM/BELLADONNA ALKALOIDS	opium	CMS and CDC
BUNAVAIL	BUPRENORPHINE HCL/NALOXONE HCL	buprenorphine	CDC only
BUPRENEX	BUPRENORPHINE HCL	buprenorphine	CDC only
BUPRENORPHINE	BUPRENORPHINE	buprenorphine	CMS and CDC
BUPRENORPHINE HCL	BUPRENORPHINE HCL	buprenorphine	CDC only
BUPRENORPHINE-NALOXONE	BUPRENORPHINE HCL/NALOXONE HCL	buprenorphine	CDC only
BUTALB-ACETAMINOPH-CAFF-CODEIN	BUTALBIT/ACETAMIN/CAFF/CODEINE	codeine	CMS and manual search
BUTALB-CAFF-ACETAMINOPH-CODEIN	BUTALBIT/ACETAMIN/CAFF/CODEINE	codeine	CMS and manual search
BUTALBITAL COMPOUND-CODEINE	CODEINE/BUTALBITAL/ASA/CAFFEIN	codeine	All three sources
BUTORPHANOL TARTRATE	BUTORPHANOL TARTRATE	butorphanol	CMS and CDC
BUTRANS	BUPRENORPHINE	buprenorphine	CMS and CDC
CAPITAL W-CODEINE		codeine	CMS only
CARISOPRODOL COMPOUND-CODEINE	CODEINE/CARISOPRODOL/ASPIRIN	codeine	All three sources
CARISOPRODOL-ASPIRIN-CODEINE	CODEINE/CARISOPRODOL/ASPIRIN	codeine	All three sources
CHERATUSSIN AC	GUAIFENESIN/CODEINE PHOSPHATE	codeine	Manual search only
CO-GESIC	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
CODEINE SULFATE	CODEINE SULFATE	codeine	All three sources
CONTRAVE	NALTREXONE HCL/BUPROPION HCL	morphine	CDC only
CONZIP	TRAMADOL HCL	tramadol	All three sources

Table B2: Drug Names Used to Pull Opioid-Related Prescribing from CMS Part D Prescriber PUF, D-H

Drug (Brand/Generic)	Generic Name	Opioid Type	Opioid Source
DEMEROL	MEPERIDINE HCL/PF	meperidine	All three sources
DIHYDROCODEIN-ACETAMINOPH-CAFF	DHCODEINE BT/ACETAMINOPHN/CAFF	dihydrocodeine	CMS and CDC
DILAUDID	HYDROMORPHONE HCL/PF	hydromorphone	All three sources
DILAUDID-5		meperidine	CDC and manual search
DILAUDID-HP	HYDROMORPHONE HCL/PF	hydromorphone	CDC and manual search
DIPHENOXYLATE W/ATROPINE		diphenoxylate	Manual search only
DIPHENOXYLATE-ATROPINE	DIPHENOXYLATE HCL/ATROPINE	diphenoxylate	Manual search only
DISKETS	METHADONE HCL	methadone	All three sources
DOLOPHINE HCL	METHADONE HCL	methadone	All three sources
DURAGESIC	FENTANYL	fentanyl	All three sources
DURAMORPH	MORPHINE SULFATE/PF	morphine	CDC and manual search
EMBEDA	MORPHINE SULFATE/NALTREXONE	morphine	CMS and CDC
ENDOCET	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
ENDODAN	OXYCODONE HCL/ASPIRIN	oxycodone	All three sources
ETH-OXYDOSE		oxycodone	CDC only
EVZIO	NALOXONE HCL	naloxone	CDC and manual search
EXALGO	HYDROMORPHONE HCL	hydromorphone	All three sources
FENTANYL	FENTANYL	fentanyl	All three sources
FENTANYL CITRATE	FENTANYL CITRATE/PF	fentanyl	All three sources
FENTORA	FENTANYL CITRATE	fentanyl	All three sources
FIORICET WITH CODEINE	BUTALBIT/ACETAMIN/CAFF/CODEINE	codeine	All three sources
FIORINAL WITH CODEINE #3	CODEINE/BUTALBITAL/ASA/CAFFEIN	codeine	All three sources
GUAIFENESIN-CODEINE		codeine	Manual search only
HYCET	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
HYDROCODONE BIT-IBUPROFEN	HYDROCODONE/IBUPROFEN	hydrocodone	All three sources
HYDROCODONE BT-HOMATROPINE MBR	HYDROCODONE BIT/HOMATROP ME-BR	hydrocodone	CDC and manual search
HYDROCODONE-ACETAMINOPHEN	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
HYDROCODONE-CHLORPHENIRAMINE	HYDROCODONE/CHLORPHEN POLIS	hydrocodone	CDC and manual search
HYDROCODONE-CHLORPHENIRAMNE ER	HYDROCODONE/CHLORPHEN P-STIREX	hydrocodone	CDC and manual search
HYDROCODONE-HOMATROPINE		hydrocodone	Manual search only
HYDROCODONE-HOMATROPINE MBR	HYDROCODONE BIT/HOMATROP ME-BR	hydrocodone	CDC and manual search
HYDROCODONE-IBUPROFEN	HYDROCODONE/IBUPROFEN	hydrocodone	All three sources
HYDROGESIC		hydrocodone	CDC only
HYDROMET	HYDROCODONE BIT/HOMATROP ME-BR	hydrocodone	CDC and manual search
HYDROMORPHONE ER	HYDROMORPHONE HCL	hydromorphone	All three sources
HYDROMORPHONE HCL	HYDROMORPHONE HCL/PF	hydromorphone	All three sources
HYSINGLA ER	HYDROCODONE BITARTRATE	hydrocodone	CMS and CDC

Table B2: Drug Names Used to Pull Opioid-Related Prescribing from CMS Part D Prescriber PUF, I-Oxe

Drug (Brand/Generic)	Generic Name	Opioid Type	Opioid Source
IBUDONE	HYDROCODONE/IBUPROFEN	hydrocodone	All three sources
INFUMORPH	MORPHINE SULFATE/PF	morphine	CDC and manual search
KADIAN	MORPHINE SULFATE	morphine	All three sources
LAZANDA	FENTANYL CITRATE	fentanyl	All three sources
LEVORPHANOL TARTRATE	LEVORPHANOL TARTRATE	levorphanol	All three sources
LOMOTIL	DIPHENOXYLATE HCL/ATROPINE	diphenoxylate	Manual search only
LORCET	HYDROCODONE/ACETAMINOPHEN	hydrocodone	CMS and CDC
LORCET 10-650	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
LORCET HD	HYDROCODONE/ACETAMINOPHEN	hydrocodone	CMS and CDC
LORCET PLUS	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
LORTAB	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
MAGNACET	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
MAXIDONE		hydrocodone	CMS and CDC
MEPERIDINE HCL	MEPERIDINE HCL/PF	meperidine	All three sources
MEPERITAB	MEPERIDINE HCL	meperidine	All three sources
METHADONE HCL	METHADONE HCL	methadone	All three sources
METHADONE INTENSOL	METHADONE HCL	methadone	All three sources
METHADOSE	METHADONE HCL	methadone	All three sources
MORPHABOND ER	MORPHINE SULFATE	morphine	CMS and CDC
MORPHINE SULFATE	MORPHINE SULFATE/PF	morphine	All three sources
MORPHINE SULFATE ER	MORPHINE SULFATE	morphine	All three sources
MOTOFEN	DIFENOXIN HCL/ATROPINE SULFATE	difenoxin	Manual search only
MS CONTIN	MORPHINE SULFATE	morphine	All three sources
NALOXONE HCL	NALOXONE HCL	naloxone	CDC and manual search
NALTREXONE HCL	NALTREXONE HCL	naltrexone	CDC and manual search
NARCAN	NALOXONE HCL	pentazocine	CDC only
NORCO	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
NUCYNTA	TAPENTADOL HCL	tapentadol	All three sources
NUCYNTA ER	TAPENTADOL HCL	tapentadol	All three sources
ONSOLIS		fentanyl	CDC and manual search
OPANA	OXYMORPHONE HCL	oxymorphone	All three sources
OPANA ER	OXYMORPHONE HCL	oxymorphone	All three sources
OPIUM		opium	CDC only
ORAMORPH SR		morphine	CDC only
OXAYDO		oxycodone	CMS only
OXECTA	OXYCODONE HCL	oxycodone	All three sources

Table B2: Drug Names Used to Pull Opioid-Related Prescribing from CMS Part D Prescriber PUF, Oxy-S

Drug (Brand/Generic)	Generic Name	Opioid Type	Opioid Source
OXYCODONE CONCENTRATE	OXYCODONE HCL	oxycodone	All three sources
OXYCODONE HCL	OXYCODONE HCL	oxycodone	All three sources
OXYCODONE HCL ER	OXYCODONE HCL	oxycodone	All three sources
OXYCODONE HCL-ACETAMINOPHEN	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
OXYCODONE HCL-ASPIRIN	OXYCODONE HCL/ASPIRIN	oxycodone	All three sources
OXYCODONE HCL-IBUPROFEN	IBUPROFEN/OXYCODONE HCL	oxycodone	All three sources
OXYCODONE-ACETAMINOPHEN	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
OXYCODONE-ASPIRIN		oxycodone	CMS and manual search
OXYCONTIN	OXYCODONE HCL	oxycodone	All three sources
OXYMORPHONE HCL	OXYMORPHONE HCL	oxymorphone	All three sources
OXYMORPHONE HCL ER	OXYMORPHONE HCL	oxymorphone	All three sources
PENTAZOCINE-ACETAMINOPHEN	PENTAZOCINE HCL/ACETAMINOPHEN	pentazocine	All three sources
PENTAZOCINE-NALOXONE HCL	PENTAZOCINE HCL/NALOXONE HCL	pentazocine and naxolone	All three sources
PERCOCET	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
PERCODAN		oxycodone	CMS and CDC
PRIMLEV	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
PROMETHAZINE VC-CODEINE	PROMETHAZINE/PHENYLEPH/CODEINE	codeine	Manual search only
PROMETHAZINE-CODEINE	PROMETHAZINE HCL/CODEINE	codeine	Manual search only
REPREXAIN	HYDROCODONE/IBUPROFEN	hydrocodone	All three sources
REVIA		naltrexone	Manual search only
ROXICET	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
ROXICODONE	OXYCODONE HCL	oxycodone	All three sources
ROXICODONE INTENSOL		oxycodone	CDC and manual search
RYBIX ODT	TRAMADOL HCL	tramadol	All three sources
RYZOLT		tramadol	All three sources
STAGESIC	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
SUBLIMAZE	FENTANYL CITRATE/PF	fentanyl	CDC and manual search
SUBOXONE	BUPRENORPHINE HCL/NALOXONE HCL	buprenorphine	CDC only
SUBSYS	FENTANYL	fentanyl	All three sources
SUBUTEX		buprenorphine	CDC only
SUFENTA	SUFENTANIL CITRATE	sufentanil	Manual search only
SUFENTANIL CITRATE		sufentanil	Manual search only
SYNALGOS-DC	DIHYDROCODEINE/ASPIRIN/CAFFEIN	dihydrocodeine	All three sources

Table B2: Drug Names Used to Pull Opioid-Related Prescribing from CMS Part D Prescriber PUF, T-Z

Drug (Brand/Generic)	Generic Name	Opioid Type	Opioid Source
TALWIN	PENTAZOCINE LACTATE	pentazocine	Manual search only
THERATRAMADOL-60		tramadol	CMS only
TRAMADOL HCL	TRAMADOL HCL	tramadol	All three sources
TRAMADOL HCL ER	TRAMADOL HCL	tramadol	All three sources
TRAMADOL HCL-ACETAMINOPHEN	TRAMADOL HCL/ACETAMINOPHEN	tramadol	All three sources
TREZIX	DHCODEINE BT/ACETAMINOPHN/CAFF	dihydrocodeine	All three sources
TUSSICAPS	HYDROCODONE/CHLORPHEN POLIS	hydrocodone	CDC and manual search
TUSSIGON	HYDROCODONE BIT/HOMATROP ME-BR	hydrocodone	CDC and manual search
TUSSIONEX	HYDROCODONE/CHLORPHEN POLIS	hydrocodone	CDC and manual search
TYLENOL-CODEINE NO.3	ACETAMINOPHEN WITH CODEINE	codeine	All three sources
TYLENOL-CODEINE NO.4	ACETAMINOPHEN WITH CODEINE	codeine	All three sources
TYLOX		oxycodone	CMS and CDC
ULTRACET	TRAMADOL HCL/ACETAMINOPHEN	tramadol	CMS and CDC
ULTRAM	TRAMADOL HCL	tramadol	CMS and CDC
ULTRAM ER	TRAMADOL HCL	tramadol	CMS and CDC
VICODIN	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
VICODIN ES	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
VICODIN HP	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
VICOPROFEN	HYDROCODONE/IBUPROFEN	hydrocodone	All three sources
VIVITROL	NALTREXONE MICROSPHERES	naltrexone	Manual search only
XARTEMIS XR	OXYCODONE HCL/ACETAMINOPHEN	oxycodone	All three sources
XODOL 10-300	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
XODOL 5-300		hydrocodone	CMS only
XODOL 7.5-300	HYDROCODONE/ACETAMINOPHEN	hydrocodone	CMS and CDC
XOLOX		oxycodone	CDC only
XTAMPZA ER	OXYCODONE MYRISTATE	oxycodone	CMS and CDC
XYLON 10	HYDROCODONE/IBUPROFEN	hydrocodone	All three sources
ZAMICET	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources
ZERLOR		dihydrocodeine	CDC only
ZOHYDRO ER	HYDROCODONE BITARTRATE	hydrocodone	All three sources
ZOLVIT		hydrocodone	CMS only
ZUBSOLV	BUPRENORPHINE HCL/NALOXONE HCL	buprenorphine	CDC only
ZYDONE	HYDROCODONE/ACETAMINOPHEN	hydrocodone	All three sources