Flipping the Script: the effects of opioid prescription monitoring on specialty-specific provider behavior *

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Abstract

Mandatory access Prescription Drug Monitoring Programs (MA-PDMPs) aim to curb the epidemic at a common point of initiation of use, the prescription. However, there is recent concern about whether opioid policies have been too restrictive and reduced appropriate access to patients with need for opioid pharmaceuticals. We assess MA-PDMP's effect on specialty-specific opioid prescribing behavior of Medicare providers. Our findings suggest that requiring providers to query a PDMP differentially affects opioid prescribing across provider specialties. We find a 3-4% decrease in prescribing for Primary Care and Internal Medicine providers. This result is driven by healthcare providers at the lower end of the prescribing distribution. There is also suggestive evidence of an increase in opioid use disorder treatment drugs prescribed by these same providers. We also find no evidence for the hypothesis that MA-PDMPs restrict prescribing by providers who treat patients with potentially high levels of pain, few drug substitutes, or urgency for pain treatment (e.g., Oncology/Palliative care). This result is not dependent on whether a state provides exemptions for these providers. 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.

Keywords: Prescription Drug Monitoring, Drug/Opioid Use, Health Policy, Provider Decision-making
JEL *Classification:* I12: Health Behavior, K32: Energy, Environmental, Health and Safety Law

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)].

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State-specific efforts to directly quell negative effects of the epidemic include 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 those individuals who **need** medicine for legitimate reasons [Dalal and Bruera (2019a) 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 is mandatory access prescription drug monitoring programs (MA-PDMP). MA-PDMPs require prescribers to query an electronic database prior to prescribing a controlled substance, but they generally do not directly dictate what a prescriber must do with information from this query. This paper examines the impact of MA-PDMPs on opioid prescribing by providers in different specialties who treat a variety of patients. We use data on over 315,068 U.S. providers and over 436.4 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 differs across specialties, we estimate heterogeneous policy 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 number 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

[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)].

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 without needlessly restricting access for those who may require it. There are four primary contributions of our work. First, this is the first study to estimate the heterogeneous effects of MA-PDMPs on changes in opioid prescribing across specialties. Given the considerable differences in opioid prescribing across specialties [Guy and Zhang (2018)], 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. Second, our data allows us to consider national provider patterns of opioid prescribing which is distinct from other studies examining doctor-shopping and initial opioid prescriptions [Sacks et al. (2019)]. We are also able to complement Buchmueller et al. (2019) by not only examining provider-level data, but by covering a longer time period during which several states passed PDMP mandates. More recent mandates tend to be more comprehensive than the earlier ones, and it is an empirical question of whether they have been as effective. Third, we examine the heterogenous distributional effects of MA-PDMPs on prescribing within provider specialties (i.e., high versus low prescribers). Lastly, we contribute to the MA-PDMP literature by evaluating whether there is any transition towards opioid use disorder treatment drugs.

Our analysis uses a difference-in-differences (DD) and event-study design 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 to 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 differences in opioid prescribing in response to MA-PDMPs across type of specialty. We find that Primary Care providers prescribe fewer opioids once a MA-PDMP is implemented. These physicians decrease prescribing by about 4 percent (about 11 fewer prescriptions per year). We also find evidence of a decrease in prescribing among Internal and Emergency Medicine prescribers; a finding that is particularly salient four-years after an MA-PDMP is in place. The decrease among these three types of providers seems to be driven by those at the lower end of the prescribing distribution. We also find that MA-PDMPs do not affect providers who treat patients with potentially high levels of pain, few drug substitutes, or urgency for pain treatment (e.g., Oncology/Palliative care).

Our results are robust after adjusting for the implementation of other opioid policies, like prescription limit and pain clinic laws, that may influence prescribing, as well as varying state law exemptions under certain circumstances or for specific providers. In examining these additional policies we demonstrate that MA-PDMPS are a flexible infrastructure improvement that are less likely to lead to unintended consequences than blunt policy instruments like prescription limit laws. In fact, we find suggestive evidence of an increase in opioid use disorder treatment drugs prescribed by Primary Care, Internal Medicine, and Emergency Medicine providers indicating that these infrastructure improvements may have additional benefits. Lastly, our findings are also robust to a series of robustness checks that adjust exclusion criteria both for providers and for opioid drugs.

We provide further evidence that the mandatory query is a salient policy to influence opioid prescribing. Our study adds additional context showing that healthcare providers are not impacted homogeneously by MA-PDMPs. In addition, our findings indicate that MA-PDMPs have likely not led to an unintentional reduction in the access of opioids for patients most in need of these types of pharmaceuticals. The PDMP information infrastructure alongside the mandate provides both flexibility and accountability that enables providers to provide informed care for their patients. This stands in stark contrast to policies like prescription limit laws which limit initial prescriptions and as we show are more likely to lead to reductions in opioid prescriptions even in cases where they may be needed. Our work demonstrates that MA-PDMPs can combat the harmful effects of the opioid epidemic and potentially aid in directing those with substance use disorders to treatment without restricting these drugs to those with the most need for them.

2 Background and Related Literature

2.1 Existing MA-PDMP evidence and critical gaps

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 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. (2016)].

There is a growing concern in states where querying the PDMP is not mandatory 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 studies in the prior decade 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)]. 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. More recent work by Sacks et al. (2019) suggests that the mandate has negligible effects on initial prescriptions.

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 utilizing multiple providers for opioid prescriptions (sometimes referred to as doctor shopping). Buchmueller and Carey (2018) focus on a subset of patients who over-use opioids, not the entire Medicare population.[2] 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 query state) and Indiana (a voluntary query state). They find a stark decrease in prescribing associated with the mandate, particularly among

[2]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.

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 specialties, 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. Therefore, we conduct sub-sample analyses by different groups of providers to tease out potential specialty-specific prescribing differences that may exist in response to PDMP implementation or identify potential unintended consequences of the policy. Lastly, states have recently begun to consider whether MA-PDMP legislation may be too restrictive, particularly for patients with terminal illnesses. For instance, Graetz et al. (2020) finds that MA-PDMPs may be associated with a decrease in opioid prescribing among oncology patients. We also consider whether these exemptions affect our findings when examining Palliative Care or Oncology providers.

2.2 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 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 simultaneously. 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 on Drug Abuse (2015)] suggesting that opioid prescribing in the Medicare population is likely to spillover to other demographic groups. 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 and other state-level policies on opioid prescribing, we study the prescribing behavior of 315,068 healthcare providers for Medicare Part D beneficiaries from 2010-2017. We obtained CMS Part D prescriber public use files (PUFs) from 2010-2017.[3] We analyzed data on opioid prescribing for 106,067 Primary Care providers, 89,930 Internal Medicine providers, 42,351 Emergency Medicine providers, 66,081 surgical providers, 14,378 Palliative care & Oncology providers, and 4,590 Pain Medicine providers.[4] The listed specialties are provided in Table B1. About 42 percent of providers are observed in all years of the sample. We excluded observations from the provider prescribing data if: (1) there was no unique prescriber identifier, either national provider identifier (NPI) or Drug Enforcement Agency (DEA) identifier; (2) the provider's listed location was in a U.S. territory or not provided; (3) the provider's listed specialty is not licensed to prescribe opioid medications; (4) the provider's listed specialty is not considered in this study. Omitted specialties are listed in Table B2. We supplemented provider prescribing data with provider location information from records of the Physician Masterfile, maintained by the American Medical

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

Association (AMA) and purchased through a database licensing agreement,[5] and we obtained PDMP mandate implementation dates from the Prescription Drug Abuse Policy System [Center for Public Health Law Research (2017)]. This use of secondary, publicly available data is not considered human subjects research by the University of Washington and does not require Institutional Review Board review or approval.

3.2 Outcomes

The primary outcome in our analysis is the annual number of opioid prescriptions, original and refill, dispensed to Medicare Part D beneficiaries by a given provider. 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 Table B3 in the Appendix. A limitation of the Medicare PUF data is that when a prescriber has 10 or fewer prescriptions for any given drug in any given year, the provider-drug record is excluded from PUFs to protect the privacy of Medicare beneficiaries. These privacy rules result in an unbalanced panel. In validity assessments and sensitivity analyses, we consider whether missingness or attrition in the data due to these privacy rules is correlated with MA-PDMP implementation or leads to a bias in estimates or in the size of standard errors. We also discuss this truncation issue along with accompanying specification checks in robustness checks and discuss in more detail in the Appendix.

3.3 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 states where a query is voluntary and states without a PDMP. We omit all providers practicing in Louisiana and Nevada from all analyses because they implemented a MA-PDMP in 2007 and 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 thus are included in our control group. Table A1 in the Appendix provides months and years of MA-PDMP implementation. We consider the effects of PDMPs when they became operational, rather than

[5]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.

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 MA-PDMP becomes operational ensures that prescribers can and must access query results and use information from the PDMP database in their prescribing decisions.

3.4 Estimation Strategy

To measure the effect of MA-PDMPs on the prescribing behavior of providers, we employ a standard differences-in-differences (DD) design with event-study analyses using Poisson.[6] This econometric approach compares the prescribing behavior of providers practicing in a state where a MA-PDMP is implemented during the study period to the behavior of those practicing in states without a MA-PDMP. A provider's prescribing behavior is given by

$$E\Big[Y_{ist}|\mathbf{W}_{ist}\Big] = \exp\Big(\mathbf{W}_{ist}\Big) \tag{1}$$

$$\mathbf{W}_{ist} = \alpha_i + \gamma_s + \theta_t + \beta\text{Post-MA-PDMP}_{st} \tag{2}$$

where Y_{ist} is the total number of opioid prescriptions written by prescriber i in state s in year t. α_i denotes provider fixed effects, γ_s denotes states fixed effects and θ_t denotes year fixed effects. Post-MA-PDMP$_{st}$ represents the MA-PDMP post-implementation treatment effect where states implement at varying years during the study period. We stratify all specifications by provider specialty. We cluster standard errors at the state-level as this is the level of policy implementation Bertrand et al. (2004) and to minimize issues from having an overpowered sample [Datta and Dave (2017)].[7]

A key identifying assumption for this empirical strategy is the parallel trends assumption. To provide evidence on the validity of this assumption, we conduct event study analyses using the same specification in equation (1) and (2) but replace the DD treatment effect, Post-MA-PDMP$_{st}$, with time to and time since treatment indicators as given in Equation 3.

$$\mathbf{W}_{ist} = \alpha_i + \gamma_s + \theta_t + \sum_j \beta_j \mathbf{1}\left\{t - \mathrm{Z}_s = j\right\} \tag{3}$$

where $j = -5, ..., 5$ and Z_s takes the value of the year of MA-PDMP implementation for state s. In presenting our findings we will present both the average treatment effects obtained from equation (2) along

[6] The primary outcome, Y_{ist}, is Poisson distributed. This approach does not suffer from the "incidental parameters" problem and can adequately accommodate required fixed effects [Cameron and Trivedi (2005); Correia et al. (2020)].

[7] All specifications are implemented with high-dimensional fixed effects as described in Correia et al. (2020).

with short- and intermediate-term treatment effects that summarize event-study estimates from equation (4). For the latter, we present point estimates with an indicator capturing all years prior to implementation (Pre-MA-PDMP$_{st}$), an indicator for years zero to three years after treatment (MA-PDMP-Years0-3$_{st}$), and an indicator for treatment four years or more after MA-PDMP implementation (MA-PDMP-Years$\geq$4$_{st}$).

$$\begin{aligned}\mathbf{W}_{ist} = \alpha_i + \gamma_s + \theta_t + \beta_0 \text{Pre-MA-PDMP}_{st} + \\ \beta_1 \text{MA-PDMP-Years0-3}_{st} + \beta_2 \text{MA-PDMP-Years}\geq 4_{st}\end{aligned} \tag{4}$$

Another 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.

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. Guy and Zhang (2018) show considerable differences in opioid prescribing across specialties in 2016-2017, with Family Medicine and Internal Medicine accounting for around 37.1 percent of all opioid prescriptions. 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)].

Table 1: Opioid Prescribing Statistics by Specialty

(a) Annual number of prescriptions per provider

Specialty	Mean	Std Dev	Min	Max	N
Primary Care	248.9	361.7	11	11,431	106,067
Internal Medicine	243.9	357.0	11	14,952	89,930
Emergency Medicine	62.4	129.4	11	8,702	42,351
Surgery	139.3	388.8	11	19,296	66,081
Palliative Care & Oncology	94.9	123.6	11	3,632	14,378
Pain Medicine	1113.8	1545.7	11	24,637	4,590
Total	192.9	399.5	11	24,637	315,068

(b) Number of distinct opioid drugs per provider

Specialty	Mean	Std Dev	Min	Max
Primary Care	3.9	2.7	1	25
Internal Medicine	3.8	2.7	1	23
Emergency Medicine	1.7	1.1	1	26
Surgery	2.3	2.0	1	27
Palliative Care & Oncology	3.1	2.2	1	16
Pain Medicine	8.5	4.6	1	32
Total	3.1	2.6	1	32

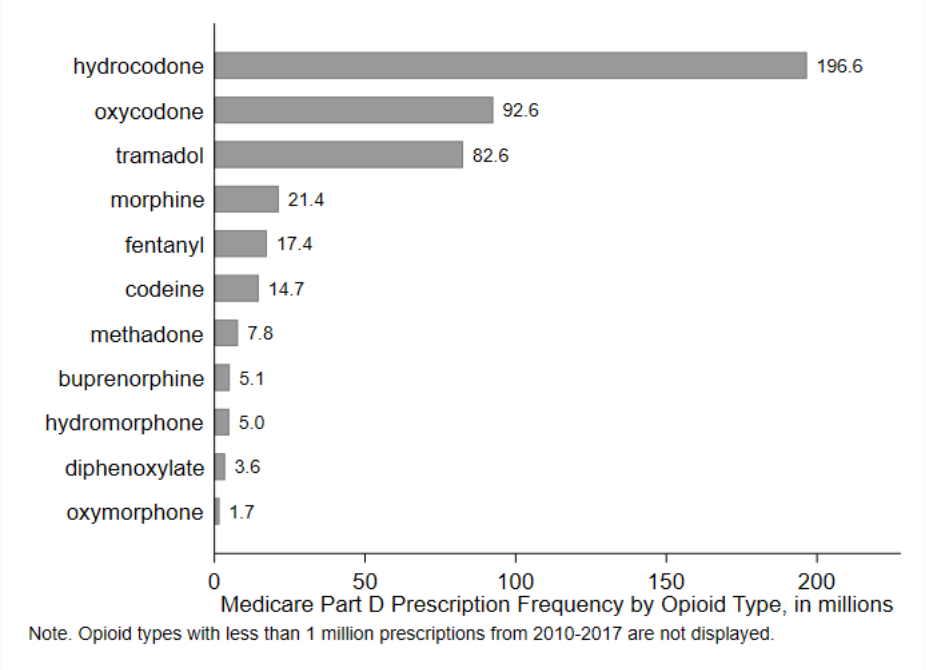
3.5 Descriptive and Summary Statistics

Figure 1 illustrates the 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 B4), 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 1 presents summary statistics for opioid prescribing variables. These statistics highlight a key issue in opioid prescribing. The mean number of annual opioid prescriptions per provider is about 193, but the magnitude of the difference between the highest and lowest is large, ranging from 11 to 24,637 prescriptions per year. This is driven both by differences between providers as well as differences between drugs. 67.2 percent of providers in our sample prescribe less than 50 total opioid prescriptions per year in at least one year in our sample. Around 4.3 percent prescribe more than 1,000 opioid per year in at least one year.

It is clear from Table 1a and 1b that opioid prescribing varies by specialty. Not surprisingly, providers in Pain Management prescribe the most opioids on average (Table 1a). We also see that there is a correlation between the number of prescriptions and the number of distinct drugs prescribed (Table 1b). Pain

Figure 1: Medicare Part D Prescription Frequency for Opioids by Type (in millions), 2010-2017



Management providers use a wider array of opioid drugs, 8.5 distinct drugs on average compared to Surgery and Emergency Medicine providers at 2.3 and 1.7 distinct drugs on average, respectively. Interestingly, Primary Care providers prescribe the second most opioids on average, while Emergency Medicine, Palliative Care, and 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. These descriptive statistics support our approach of stratification by specialty.

4 Results

4.1 Validity

4.1.1 Event study evaluation of parallel trends assumption

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 must exhibit parallel trends with non-MA-PDMP states prior to implementation of the MA-PDMP. We provide evidence to support this assumption using an event study design, depicted in Figure 2. We present the estimated coefficients and 95 percent confidence intervals from equation (3) stratified by specialty. We find

no evidence of violations of the parallel trends assumption in any sub-sample analysis. Both Buchmueller and Carey (2018) and Dave et al. (2017) also use this quasi-random approach to study other opioid-related outcomes including opioid misuse, utilizing multiple providers for opioid prescriptions among Medicare Part D beneficiaries, and opioid treatment admissions into substance abuse facilities.

We observe reductions in opioid prescribing in most post-implementation years among Primary Care providers (Figure 2a) and Internal Medicine providers (Figure 2b). For both types of providers, decreases in prescribing occur as soon as the policy is implemented, and reductions in prescribing persist and expand in magnitude over time. Although they continue to prescribe fewer opioids compared to non MA-PDMP providers, the confidence intervals for some post-implementation years widen over time due to a loss of precision because fewer states and providers are used to estimate effects for each additional year after MA-PDMP implementation. We also observe declining trends in opioid prescribing among Emergency Medicine providers and Pain Medicine providers; however, the effects are less abrupt and less precisely estimated in our sample. Palliative Care and Oncology providers along with surgical providers do not significantly alter their prescribing after the implementation of MA-PDMPs.

4.1.2 Potential measurement error due to truncation

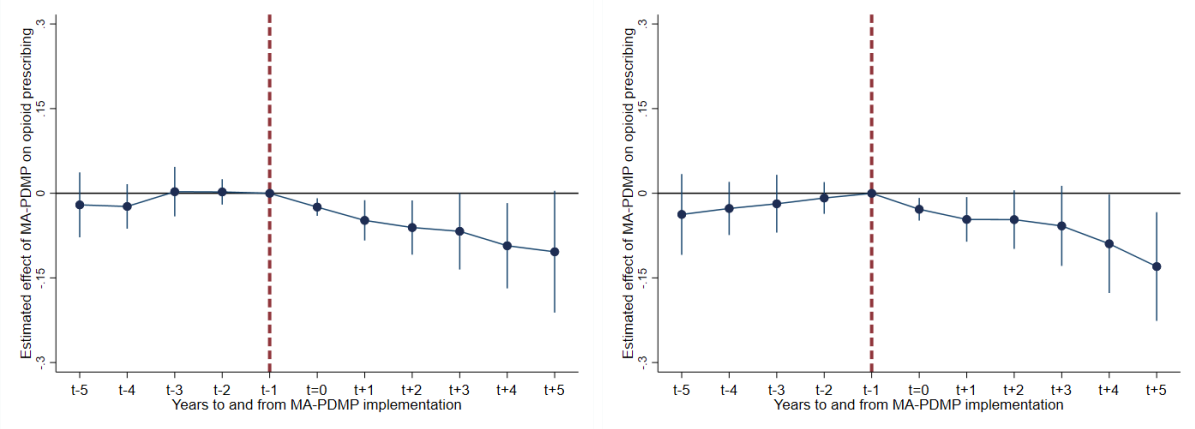
Another key concern in our approach and in the use of CMS Part D PUFs is that the truncation that occurs for beneficiary privacy in the PUFs may be correlated with the implementation of MA-PDMPs. Doctors who change prescribing along either the extensive or intensive margin close to the truncation point 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

$$y_{ist} = \begin{cases} 0, & \text{if provider } i \text{ in state } s \text{ is observed in PUFs in year } t \\ 1, & \text{if provider } i \text{ in state } s \text{ is unobserved in PUFs in year } t \end{cases} \tag{5}$$

$$y_{ist} = \alpha_i + \gamma_s + \theta_t + \beta \text{Post-MA-PDMP}_{st} + \epsilon_{st} \tag{6}$$

We estimate linear probability models using ordinary least squares (OLS) to assess whether the unobserved status is correlated with the implementation of a MA-PDMP. We present these results in Figure 3 and Table A2. Overall, we find that MA-PDMP implementation is not associated with the observation status of prescribers across specialties. One exception may be Primary Care providers, where the point estimate

Figure 2: Parallel Trends: MA-PDMP Implementation



(a) Primary Care

(b) Internal Medicine

(c) Emergency Medicine

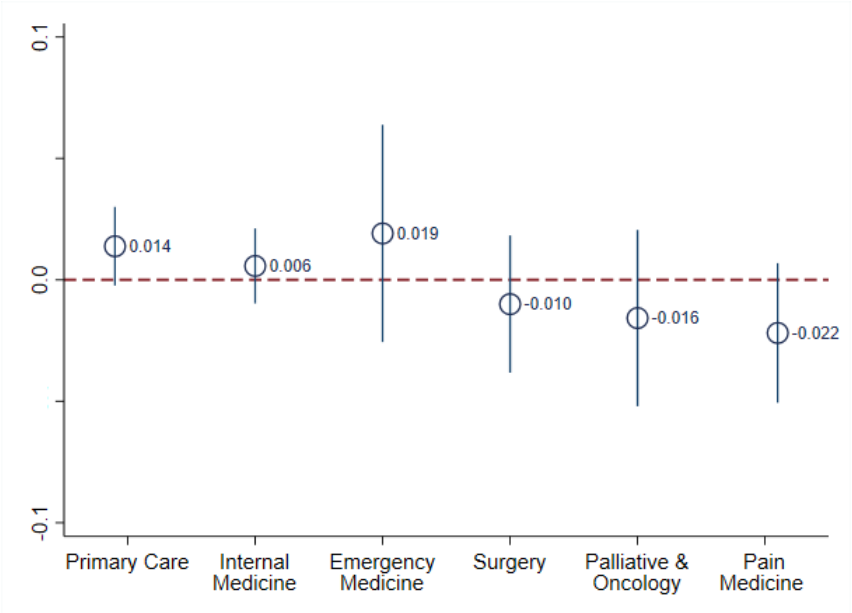
(d) Surgery

(e) Palliative Care and Oncology

(f) Pain Medicine

Note. The y-axis plots coefficient estimates and 95 percent confidence intervals from equations (1 and 3) from a Poisson regression of opioid prescriptions on indicators with years to and years since MA-PDMP implementation with state and year fixed effects. Data are provider-year level and the study period is 2010-2017.

Figure 3: Association between provider unobserved status and MA-PDMP implementation



Note. The dependent variable in each specification is a binary equal to one if provider i is unobserved in year t (provider i writes less than 10 prescriptions of any opioid drug in year t). The y-axis plots coefficient estimates and 95 percent confidence intervals of the estimated association between MA-PDMP implementation and a provider's unobserved status and the y-axis provides the specialty subsample.

is significant at the ten-percent level. However, overall this validity check suggests that providers are no more likely or less likely to be unobserved in our data. 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. In sensitivity analyses and other robustness checks, we further examine these dynamics. First, we also consider the distributional effects of MA-PDMPs on prescribing within specialties to determine if any effects are driven by prescribers at the lower end of the distribution. We replicate findings from prior work that shows low-volume prescribers stop writing opioid prescriptions altogether after an MA-PDMP was implemented in Kentucky Buchmueller et al. (2019) among some specialities. We also discuss how this finding may affect the effects on the number of prescriptions by Primary Care providers. Second, we also consider an alternate specification where we restrict our analysis to providers who we can observe throughout the entire sample period (i.e., a balanced panel). Results from these analyses are discussed further in the Robustness section.

4.2 Main Results

Table 2 presents the estimate of the effect of MA-PDMPs on the number of prescriptions for each provider, stratified by specialty. Panel A presents the joint treatment effects for the years prior to implementation, years zero to three years after treatment, and four years or more. Panel B presents the average effect of an MA-PDMP mandate. The difference in magnitude and statistical significance across specialty supports the stratification of providers. The sub-sample analysis reveals important differential effects that are consistent with event-study figures (Figure 2): There are immediate and persistent reductions in the number of opioid prescriptions following MA-PDMP implementation among Primary Care and Internal Medicine specialities. The lack of changes among Surgical, Palliative Care, Oncology, and Pain Medicine 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 Primary Care and Internal Medicine providers. Within the first three years of a MA-PDMP, Primary Care providers decrease prescribing by about 4.7% (about 12 prescriptions).[8] The longer-run effect, four or more years after the policy, the decrease is more substantial − a 9.9% decrease (24.5 prescriptions). We see a similar pattern for Internal Medicine providers. Emergency Medicine prescribers also experience a decrease that is most precisely estimated four or more years after a MA-PDMP. Specifically, about a 11% decrease (7 prescriptions).

Primary Care, Internal Medicine, and Emergency Medicine are specialties with low and 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 and extensive. 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, all of these specialties may have more readily prescribed opioids for pain.

We find little to no significant changes in the number of opioids prescribed among Surgical, Palliative Care, Oncology, or Pain Medicine providers. This result is particularly of interest given the recent concern

[8] We calculate the number of prescriptions using the means from Table 1: $(e^{\cdot 046} - 1) * 248.9 = 11.72$.

Table 2: Differential Effects of MA-PDMP Implementation on Opioid Prescribing by Provider Specialty

Dependent Variable: Number of opioid prescriptions from provider i in state s in year t

Variable	(1) Primary Care	(2) Internal Medicine	(3) Emergency Medicine	(4) Surgery	(5) Palliative Care & Oncology	(6) Pain Medicine
			Panel A: Time-varying Treatment Effect			
Pre-MA-PDMP$_{st}$	-0.009	-0.020	-0.018	0.005	-0.019	-0.005
	(0.015)	(0.019)	(0.024)	(0.027)	(0.032)	(0.028)
MA-PDMP-Years0-3$_{st}$	-0.046***	-0.043**	-0.041	-0.038	-0.012	-0.037
	(0.016)	(0.018)	(0.031)	(0.033)	(0.028)	(0.032)
MA-PDMP-Years≥4$_{st}$	-0.094**	-0.102***	-0.102**	-0.069	-0.048	-0.129*
	(0.037)	(0.039)	(0.043)	(0.081)	(0.050)	(0.077)
			Panel B: Average Treatment Effect			
Post-MA-PDMP$_{st}$	-0.043**	-0.033	-0.033	-0.042	-0.002	-0.036
	(0.021)	(0.023)	(0.037)	(0.044)	(0.038)	(0.041)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Provider fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	597,296	469,752	220,387	346,541	71,439	22,848
Providers	106,067	89,930	42,351	66,081	14,378	4,590

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 Poisson regression, and all regressions include year fixed effects, state fixed effects, and provider fixed effects. Standard errors are given in parentheses and clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

surrounding the access to opioids for patients in the most need of treatments involving controlled substances [Graetz et al. (2020), Dalal and Bruera (2019a), Yuanhong Lai et al. (2019), and Allen et al. (2020)]. Overall, these results suggest that MA-PDMPs are a salient policy that provides additional pertinent information to providers that need it without unduly restricting access to opioid medications for those who may require it.

4.3 Prescription limit laws and Pain clinic laws

MA-PDMPs are a state-level infrastructure provision that enable both the tracking and review of prescription information but do not necessarily dictate the the course of action for each patient-provider interaction. In most cases, providers retain autonomy in the decision of what to do with information from a MA-PDMP query. Prescription limit laws, on the other hand, are blunt legal instruments that pre-specify the number of days supplied or other opioid dosing components designed to directly limit the number of opioids. Limits on the length of initial prescriptions has been found to reduce the average length of initial prescriptions but increase the frequency of prescriptions [Sacks et al. (2019)]. We consider both whether our prior estimates of MA-PDMP implementation may be confounded by the implementation of prescription limit laws by

adjusting for whether a state has implemented these additional restrictions on prescribing. This also enables us to assess the policy effect differences between these two policies that both aim to address the opioid epidemic through access to prescription opioids. The vast majority of states in the MA-PDMP treatment group implemented prescription limit laws in either 2016 or 2017 (Table A4). We present estimates from this specifications in Table 3.

Our estimates for MA-PDMP implementation (Table 2) are somewhat attenuated by adjusting for these additional prescription limitations, but not entirely (Table 3, Panel A), suggesting that our prior estimates are not entirely confounded by this policy. More importantly, we find that while MA-PDMPs have no significant impact on the prescribing of surgical, Palliative Care, Oncology, and Pain Medicine providers, prescription limit laws reduce either the number of prescriptions, the number of days supplied[9] or both among these providers (Table 3, Panel A and B). These effects are most pronounced among Surgical and Pain Medicine providers. A roughly 12% (17 prescriptions) and 8% (91 prescriptions) reduction, respectively. In addition, similar to [Sacks et al. (2019)] we find that the average length of prescriptions among Part D declines after the implementation of prescription limit laws for all specialties considered in our analysis (Table 3, Panel B). For instance, Primary Care providers reduce the number of days supplied by about 5% (1.2 days per prescriptions). The most pronounced effect is for Surgery, about a 16% decrease (2.7 days per prescription). These results further support the hypothesis of MA-PDMPs filling information gaps defferentially across specialties. The prescribing limit findings are consistent with Sacks et al. (2019) in that they seem to affect all providers, whereas the MA-PDMP results are more nuanced and concentrated among certain kinds of providers. Our findings indicate that prescribers that treat patients with relatively higher 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. Instead, our results from MA-PDMPs are concentrated among Primary Care and Internal Medicine.

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)]. 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

[9]One substantial problem with studying days supplied in the Part D PUFs 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 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. Given that these results likely contain substantial measurement error, we do not focus on this variable as one of the main outcomes.

Table 3: MA-PDMP Effect after Adjusting for Initial Prescription Length Laws

Variable	(1) Primary Care	(2) Internal Medicine	(3) Emergency Medicine	(4) Surgery	(5) Palliative Care & Oncology	(6) Pain Medicine
Original Estimates, Table 2						
MA-PDMP-Years0-3$_{st}$	-0.046***	-0.043**	-0.041	-0.038	-0.012	-0.037
	(0.016)	(0.018)	(0.031)	(0.033)	(0.028)	(0.032)
MA-PDMP-Years≥4$_{st}$	-0.094**	-0.102***	-0.102**	-0.069	-0.048	-0.129*
	(0.037)	(0.039)	(0.043)	(0.081)	(0.050)	(0.077)
Panel A: Number of opioid prescriptions from provider i in state s in year t						
MA-PDMP-Years0-3$_{st}$	-0.036**	-0.036**	-0.031	-0.013	-0.002	-0.022
	(0.015)	(0.018)	(0.035)	(0.029)	(0.030)	(0.027)
MA-PDMP-Years≥4$_{st}$	-0.076**	-0.090**	-0.084*	-0.020	-0.030	-0.094
	(0.033)	(0.036)	(0.047)	(0.075)	(0.048)	(0.072)
RX Limit Law$_{st}$	-0.045*	-0.027	-0.045	-0.118***	-0.040	-0.079***
	(0.025)	(0.018)	(0.032)	(0.034)	(0.027)	(0.023)
Panel B: Number of opioid days supplied from provider i in state s in year t						
MA-PDMP-Years0-3$_{st}$	-0.040**	-0.043**	-0.007	-0.023	-0.010	-0.025
	(0.017)	(0.020)	(0.057)	(0.033)	(0.030)	(0.027)
MA-PDMP-Years≥4$_{st}$	-0.088**	-0.112***	-0.068	-0.044	-0.054	-0.100
	(0.039)	(0.034)	(0.072)	(0.108)	(0.054)	(0.073)
RX Limit Law$_{st}$	-0.053*	-0.034*	-0.074	-0.152***	-0.051*	-0.083***
	(0.028)	(0.020)	(0.054)	(0.047)	(0.027)	(0.024)
N	597,296	469,752	220,387	346,541	71,439	22,848
Providers	106,067	89,930	42,351	66,081	14,378	4,590

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 Poisson regression, and all regressions include year fixed effects, state fixed effects, and provider fixed effects as well as pre-implementation years as specified in equation 4. Standard errors are given in parentheses and clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

prescribing of Pain Management providers [Center for Public Health Law Research (2017)].[10] West Virginia does not have a separate prescription limit law like other states, and these restrictions apply only to Pain Medicine providers. However, it is not possible to isolate the impact of the WV MA-PDMP among Pain Medicine providers from the WV pain clinic law because they are both passed in 2012.

[10]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.

Table 4: Opioid Prescribing Quartiles by Specialty

Specialty	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Primary Care	0-45	46-119	120-281	282+
Internal Medicine	0-44	45-125	126-291	292+
Emergency Medicine	0-21	22-36	37-61	62+
Surgery	0-27	28-54	55-118	119+
Palliative Care & Oncology	0-25	26-53	54-107	108+
Pain Medicine	0-126	127-402	403-993	994+

Note. The number of prescriptions spanning each quartile are presented. Prescribing at baseline (2010) was used to define quartiles within each specialty classification as in Buchmueller et al. (2019).

4.4 Palliative Care & Oncology exceptions

It is possible that we do not observe significant differences in prescribing among Palliative Care & Oncology providers because in some states there are explicit exemptions for these cases. There are growing concerns that prescription drug monitoring programs may inhibit legitimate prescribing of opioids especially to Oncology and Palliative Care patients [Graetz et al. (2020), Dowell D (2019), Dalal and Bruera (2019b)]. Recently, many states are amending their MA-PDMP statutes to contain language about exemptions for certain providers and/or certain medical situations. We gathered information about these exemptions by contacting PDMP administrators in all 50 states and the District of Columbia and searching the relevant statutes and codes that contained exemptions, as well as the legislative effective date for these exemptions [Prescription Drug Monitoring Program Training and Technical Assistance Center (2021)]. Because some exemptions are either patient-specific or days-supplied-specific and our data is not granular enough to detect these nuances, we focused on exemption statutes that would apply across all patients for a given type of provider. These exemptions, their implementation, and their corresponding statutes and codes are described further and listed in Appendix A.1 (Table A5). There are five states in our study period that implement MA-PDMPs and whose statutes/codes provide exemptions for Palliative Care providers (AR, OK, VA) or both Palliative Care and Oncology providers (KY, OH) during our study period. These exemptions make MA-PDMPs less salient for these providers. Therefore, we estimate a specification where we omit providers in these states where exemptions apply. Our primary results are robust to this specification suggestion that the lack of an effect is not driven by these exemptions. Even in states that require Palliative Care & Oncology providers to query the MA-PDMP before prescribing opioids, we do not observe any changes in the opioid prescribing of these providers after MA-PDMP implementation (results are available upon request).

4.5 Low volume prescribers

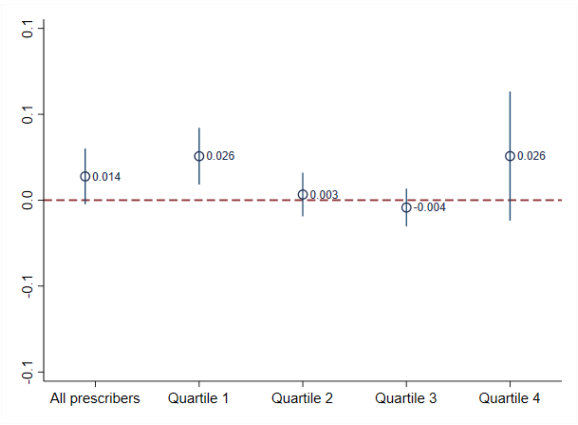
Buchmueller et al. (2019) find evidence that as many as 40 percent of low-volume prescribers stop writing opioid prescriptions altogether after the KY mandate is implemented. Because our data span a longer period of time and a larger number of states, we are well equipped to test for this exit effect and assess whether this policy effect is generalizable to other states that implement MA-PDMPs. However, given that our data is truncated we cannot truly observe whether a providers ceases to prescribe altogether. Therefore, to test whether our main findings are concentrated among low-volume prescribers we define the Medicare Part D extensive margin (MDEM) as whether or not a prescriber writes 10 or fewer prescriptions for any opioid drug (as in Figure 3). We use prescribing at baseline (2010[11]) to define prescribing quartiles within each specialty classification as in Buchmueller et al. (2019). These quartiles by specialty are provided in Table 4. On average, MA-PDMPs are not associated with whether or not a prescribers writes no more than 10 prescriptions for any opioid drug (Figure 3). Using the approach described in equations (5) and (6), Figure 4 presents results stratified by both baseline prescribing quartile and specialty. Consistent with other analyses, we observe no changes among surgical, Palliative Care, Oncology, or Pain Medicine providers regardless of prescribing quartile. However, low volume prescribing Primary Care and Internal Medicine providers (Quartile 1) are more likely to write fewer than 10 opioid prescriptions for any opioid drug. Providers in other quartiles (Quartile 2, 3, 4) are no more likely to write less than 10 opioid prescriptions for any opioid, suggesting that we can replicate the low-volume prescriber effect found in Buchmueller et al. (2019), for Primary Care and Internal Medicine providers. Essentially, we find that Primary Care and Internal Medicine providers reduce their opioid prescribing at both the MDEM extensive margin (in the Medicare Part D setting defined as writing more than 10 prescriptions for any opioid drug) and the intensive margin as demonstrated previously. Emergency Medicine providers in the first and second quartile appear to be more likely to write fewer than 10 prescriptions for any opioid drug after the implementation of MA-PDMPs. However, this result is only precisely estimated for Emergency Medicine providers in the second quartile. These effects are also overall less precisely estimated than those for Primary Care and Internal Medicine.

4.6 Opioid use disorder (OUD) medication-assisted treatment (MAT) and opioid overdose reversal drugs

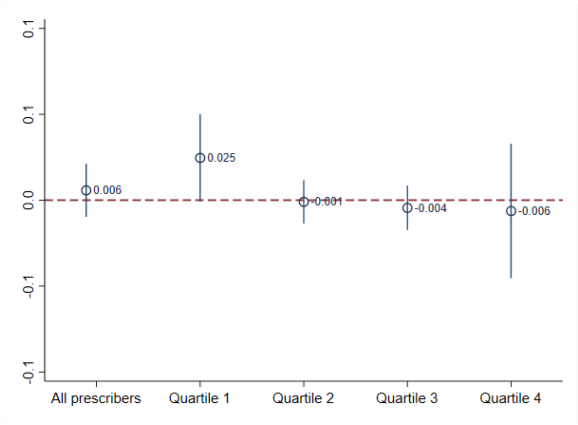
One unintended potential benefit of MA-PDMPs is whether or not they enable providers to detect or screen for opioid use disorder (OUD) and direct those patients to evidence-based treatment. Prior work has assessed

[11] Providers that are unobserved in 2010 due to truncation are included in the lowest quartile, 25^{th} percentile.

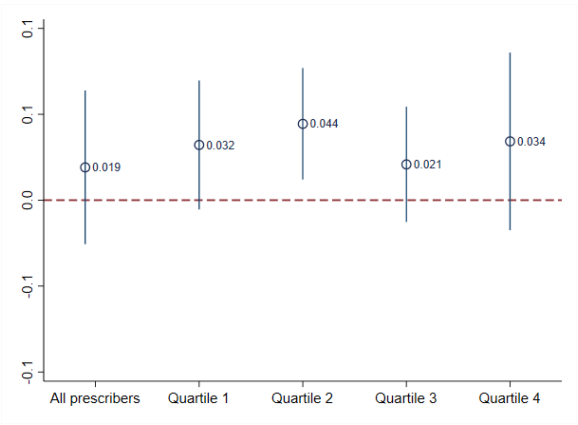
Figure 4: Association of MA-PDMP implementation with unobserved status by prescribing quartile at baseline



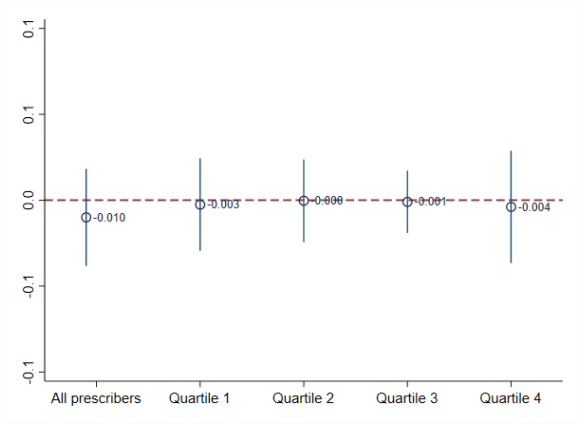
(a) Primary Care



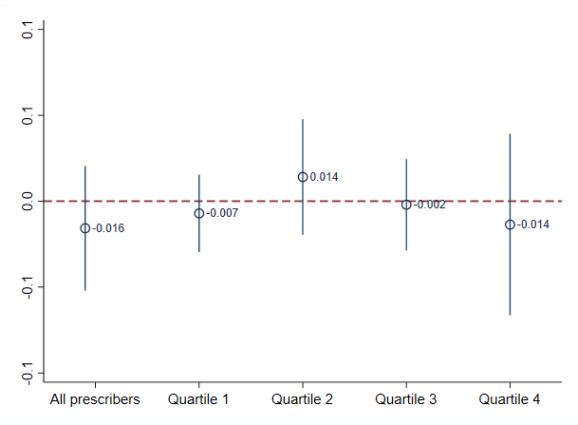
(b) Internal Medicine



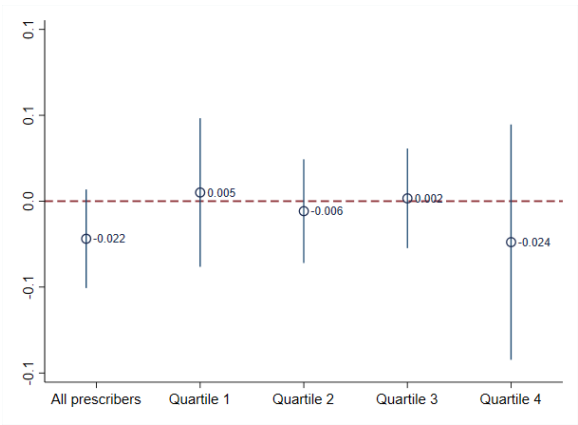
(c) Emergency Medicine



(d) Surgery



(e) Palliative Care and Oncology



(f) Pain Medicine

Note. The dependent variable in all specifications is a binary equal to one if provider i is unobserved in year t (provider i writes less than 10 prescriptions of any opioid drug in year t). The y-axis plots coefficient estimates and 95 percent confidence intervals across specialty-specific quartiles on the x-axis.

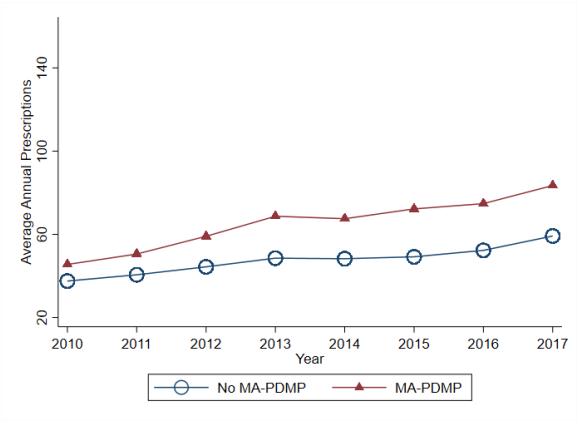
the ability of MA-PDMPs to direct patients towards substance use disorder treatment facilities [Grooms and Ortega (2019); Maclean and Saloner (2019)], but not other evidence-based interventions like medication-assisted treatment. Medication-assisted treatment (MAT) is one of the few proven strategies to reduce opioid misuse [Saloner and Barry (2018)]. However, it is largely under-utilized and is not widely prescribed by many specialties in our Medicare Part D sample. During our study period, only around 6% of prescribers in our study sample (Primary Care, Internal Medicine, Emergency Medicine, Surgery, Palliative Care & Oncology, Pain Medicine) wrote prescriptions for OUD treatment medications or opioid overdose reversal drugs like buprenorphine or naloxone. On average, only 1.24 percent of prescriptions in the Medicare Part D sample are written for these drugs.[12] These treatment regimens are more commonly prescribed among other provider specialties not considered in our main analyses. For example, OUD treatment prescriptions and opioid overdose reversal drugs and antagonists comprise 58.8 percent of prescriptions among Mental Health providers in the Medicare Part D PUFs, compared to 1.24 percent among providers in the specialties considered here.

We find suggestive descriptive evidence that providers in MA-PDMP states may prescribe OUD MAT and opioid overdose reversal drugs and antagonists more often on average than providers in non-MA-PDMP states (Figure 6). Given the limited sample size, our ability to assess the causal impact of MA-PDMPs on OUD MAT and opioid overdose reversal drug prescriptions is limited. Thus, these findings should be seen as correlations. To assess our ability to study these effects, we conducted event studies, similar to equation 3, using both a binary measure of OUD MAT and opioid overdose reversal drug prescribing (MDEM extensive margin) as well as the number of prescriptions (intensive margin) as two separate dependent variables. There is evidence of parallel trend violations among some specialties at the MDEM extensive margin (Figure 6), Internal Medicine and Emergency Medicine, and among all specialties at the intensive margin (Figure A1). In addition, the low volume of prescribing of these drugs (small sample sizes) inhibits our ability to precisely estimate the effects of MA-PDMPs for all provider specialties. Sample sizes for Palliative Care and Oncology providers are too small to estimate any effects.[13] We find evidence of associations that Primary Care, Internal Medicine, and Emergency Medicine providers may increase OUD MAT and opioid overdose reversal drug prescribing after MA-PDMP implementation. Taken together with our main opioid prescribing results, the increase in OUD MAT prescribing post-implementation of MA-PDMPs may be evidence of provider recognition of misuse among Primary Care, Internal Medicine, and Emergency Medicine patients. These

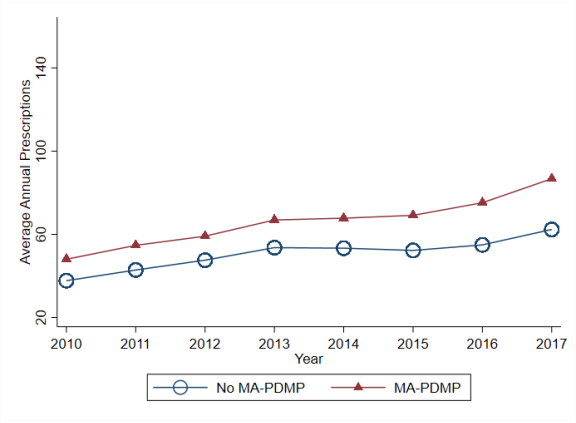
[12] 82.6 percent of these prescriptions are buprenorphine, 0.4 percent are naloxone, 13.0 percent are naltrexone, and 4.0 percent pentazocine and naloxone.

[13] In addition, the confidence intervals in Figure A1 are around double the size of those in Figure 2.

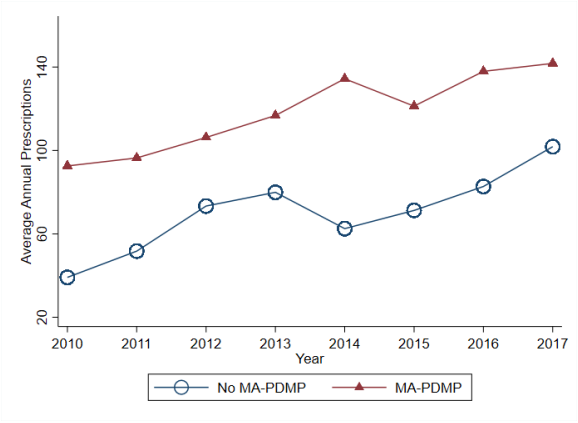
Figure 5: State-level annual average OUD MAT and opioid overdose reversal drug prescribing by provider type



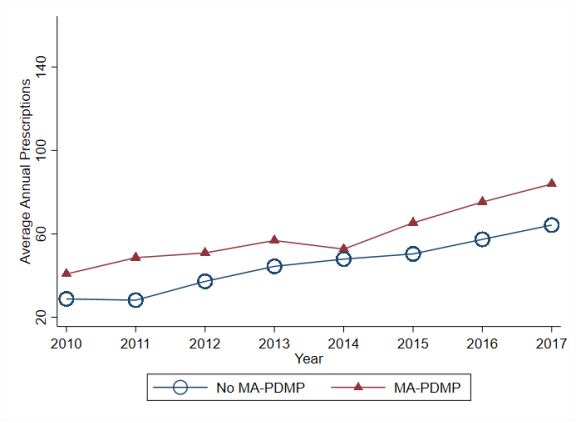
(a) Primary Care



(b) Internal Medicine



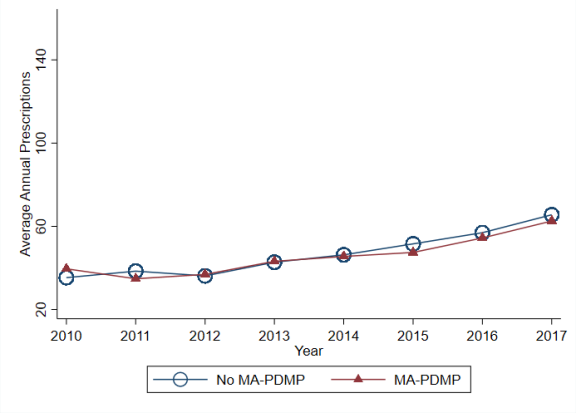
(c) Emergency Medicine



(d) Surgery

Not examined due to small sample size problems

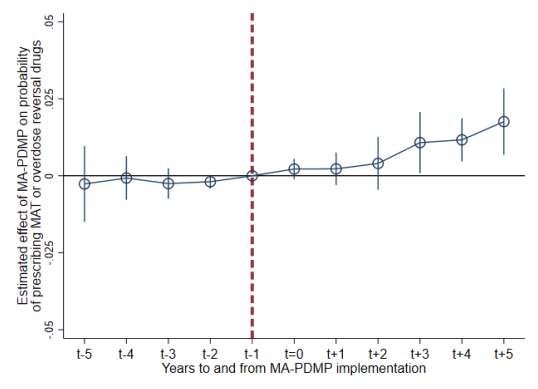
(e) Palliative Care and Oncology



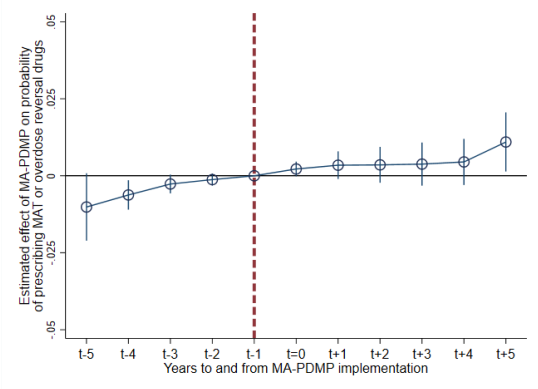
(f) Pain Medicine

Notes. Each figure reports the average annual number of prescriptions for opioid use disorder medication-assisted treatment drugs and opioid overdose reversal drugs by provider type among MA-PDMP states compared to states without MA-PDMPS.

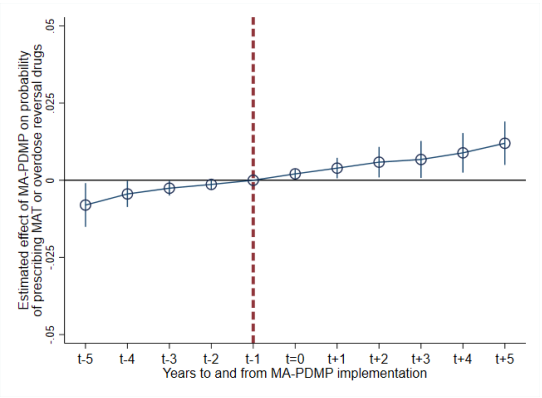
Figure 6: Event studies, OUD MAT and opioid overdose reversal drug prescribing at the extensive margin



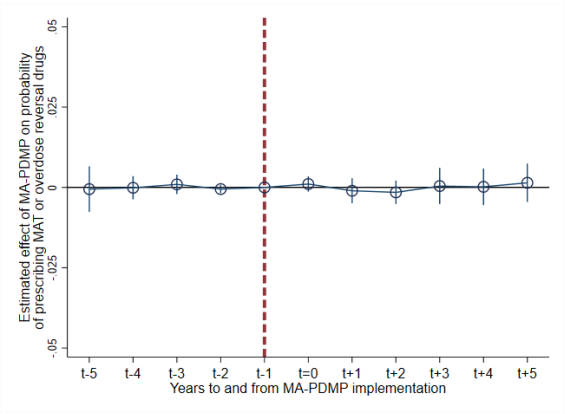
(a) Primary Care



(b) Internal Medicine



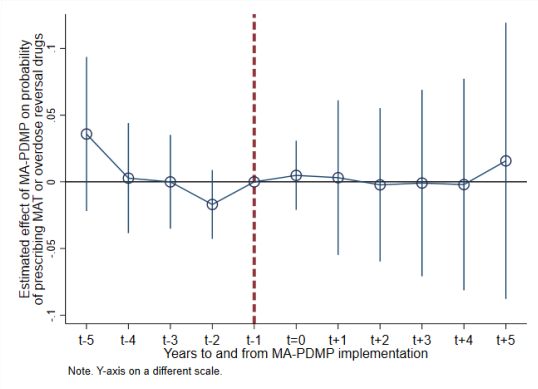
(c) Emergency Medicine



(d) Surgery

Not examined due to small sample size problems.

(e) Palliative Care and Oncology



(f) Pain Medicine

Note. The y-axis plots coefficient estimates and 95 percent confidence intervals from event study models where the dependent variable in all specifications is a binary equal to one if provider i writes 10 or more prescriptions of any OUD medication-assisted treatment drug or opioid overdose reversal drug in year t from a Linear probability regression on indicators with years to and since MA-PDMP implementation with state and year fixed effects. Data are provider-year level and the study period is 2010-2017.

findings are meaningful given the logistical and legislative barriers for providers to deliver evidence-based OUD MAT and overdose reversal resources to their patients [Roman et al. (2011); Haffajee et al. (2018)]. While it is out of the scope of this study to explore these challenges, future work should evaluate the screening potential of MA-PDMPS to identify opioid use disorders and refer patients to appropriate treatment in both low- and high-barrier settings.

5 Robustness Checks

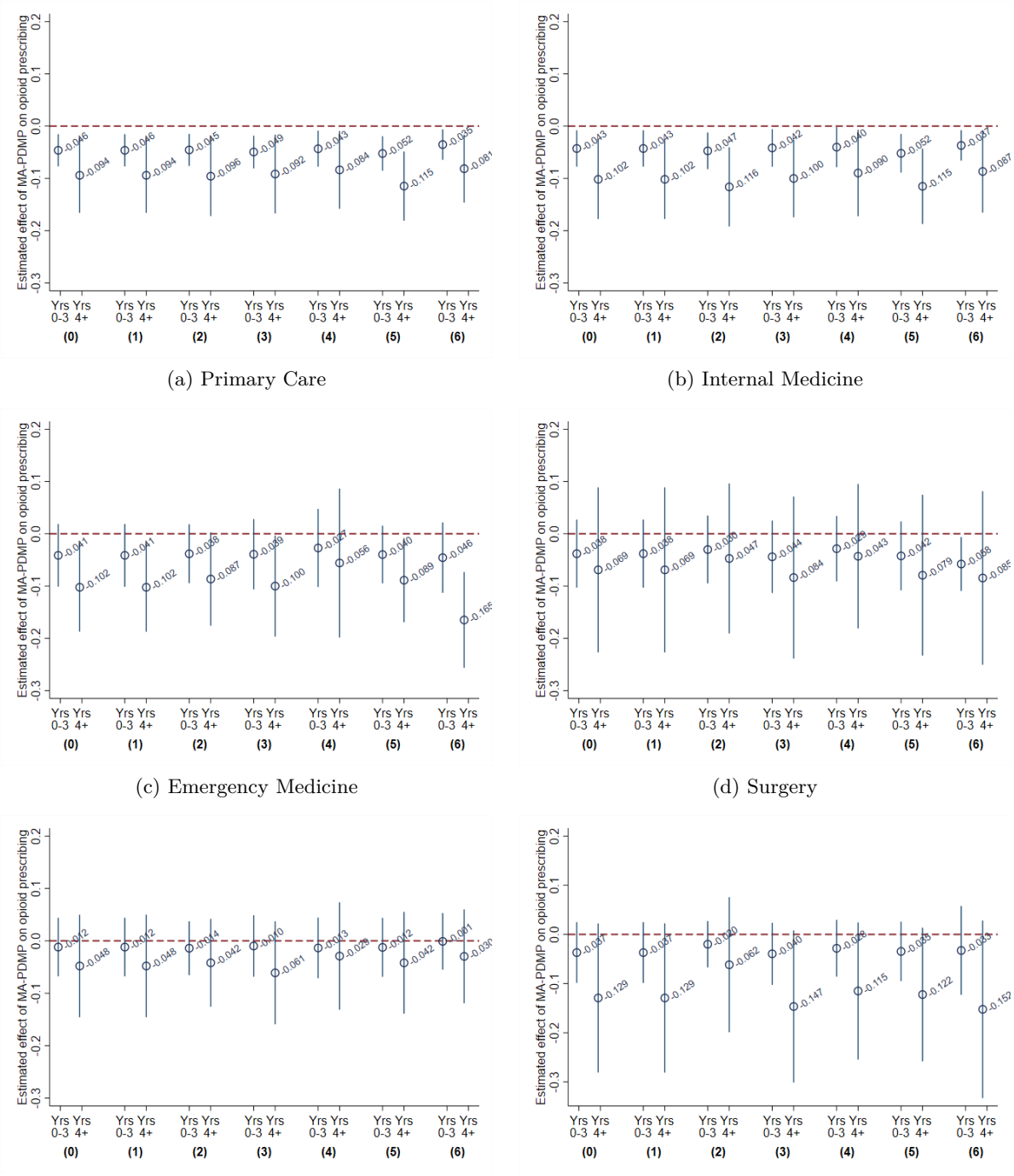
5.1 Model sensitivity analyses

We consider a number of robustness checks to bolster our primary results. We assess both the sensitivity of our results to alternative model specification, as well as the sensitivity to accounting for other opioid policies and adjusting for varying procedures for MA-PDMPs across states. To test the sensitivity of our results to alternate model specifications, we assess the following revisions to the primary specification: 1) adjusting standard errors for serial correlation at both the policy-level (state) and the prescribing-level (provider), 2) adjusting for state-level demographic information and the passage of medical marijuana laws, 3) including only providers observed in all years of the study period, 4) including only the three most common opioid types (oxycodone, hydrocodone, tramadol), 5) adjusting for the composition of opioid prescriptions by type, and 6) adjusting for truncation in the Part D PUFs. Results for these robustness checks are provided in Figure 7 and described in detail in Section A.2. Broadly, these results support our findings in Section 4.2.

5.2 Time-varying implementation of MA-PDMPs

Recent econometric work on the differences-in-differences design demonstrates that time-varying treatment can introduce bias in DID estimates (e.g., Goodman-Bacon (2018), Callaway and Sant'Anna (2020)). Given that we are using a count model with a heavily unbalanced panel we are unable to applying the weighting scheme from Goodman-Bacon (2018). However, we can limit the negative weighting of some events that may occur with a staggered DID by stacking all of the event-specific data to calculate an average effect across all events [Abraham and Sun (2018); Cengiz et al. (2019); Deshpande and Li (2019)]. This is sometimes referred to as a "stacked" difference-in-differences model. There are 22 treated states in our data. Thus, we create 22 separate groups or datasets that contains a respective treated unit and all control units over the time of our sample. We then stack all datasets into one larger stacked sample. We specify these models using

Figure 7: Effect magnitudes and confidence intervals by robustness specification



(a) Primary Care

(b) Internal Medicine

(c) Emergency Medicine

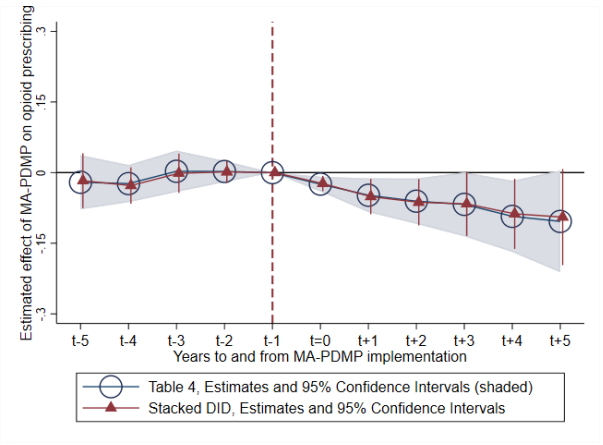
(d) Surgery

(e) Palliative Care and Oncology

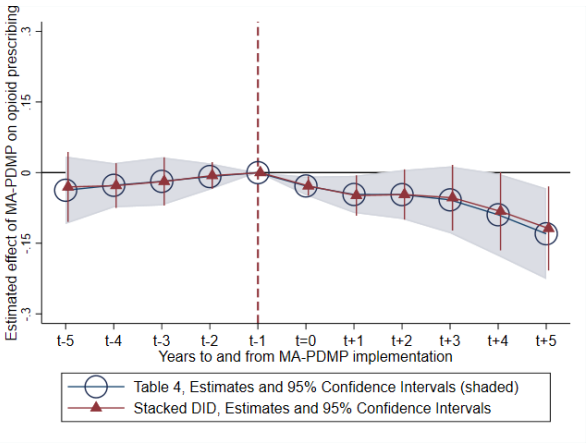
(f) Pain Medicine

Notes. The x-axis plots coefficient estimates and 95 percent confidence intervals for MA-PDMP-Years0-3$_{st}$ and MA-PDMP-Years$\geq$4$_{st}$ from various alternative specifications.
0 - Results from equation (4), 1 - Adjusting for both provider- and state-level serial correlation, 2 - Adjusting for covariates, 3 - Including only providers observed in all years, 4 - Including only the three most common opioid types, 5 - Adjusting for composition of opioids prescribed by opioid type, 6 - Adjusting for aggregate truncation proxy

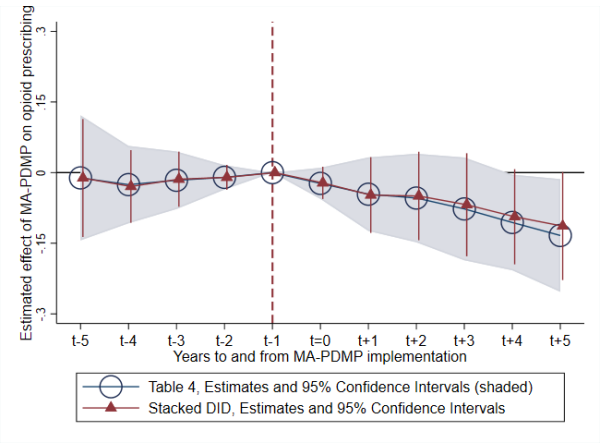
Figure 8: Stacked DID: MA-PDMP Implementation



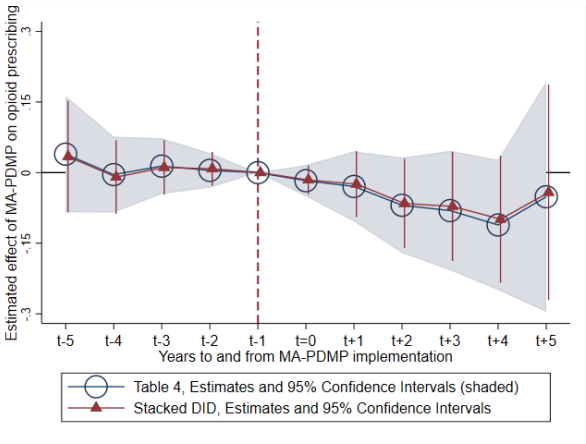
(a) Primary Care



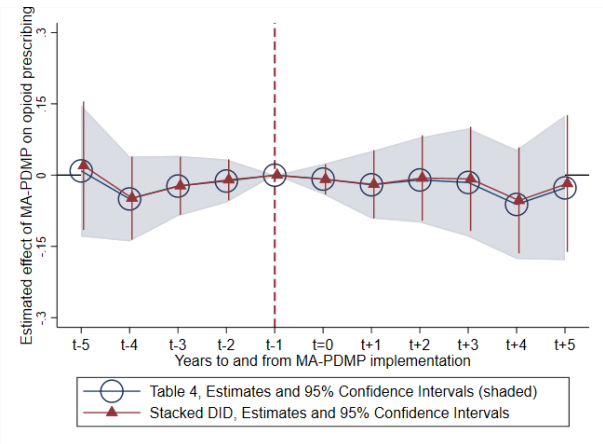
(b) Internal Medicine



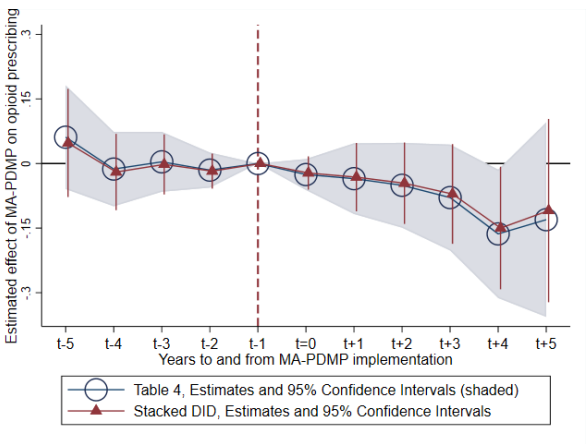
(c) Emergency Medicine



(d) Surgery



(e) Palliative Care and Oncology



(f) Pain Medicine

Note. The y-axis plots coefficient estimates and 95 percent confidence intervals using the stacked differences-in-differences model described in text.

equation (3) but also include group-year fixed effects.[14] We present these results, along with our baseline event study results, in Figure 8. Across all specialties the stacked estimates seem to mirror our main results closely. This suggests that the negative-weighting issue that is sometimes present in models with staggered timing adoption does not seem to a concern.

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 specialties 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 acute pain (e.g., Surgery, Emergency Medicine, Oncology, Palliative Care, or Pain Management). We find that MA-PDMPs decrease opioid prescribing by Primary Care and Internal Medicine providers by roughly 4% per year. We find that the decrease is most prominent in the long run with Primary Care, Internal Medicine, and Emergency Medicine providers prescribing roughly 10% fewer opioids four or more years after implementing an MA-PDMP. These results seem to be driven by providers at the lower end of the prescribing distribution. Among these providers, where we observe a decrease in opioid prescribing, we also find suggestive evidence of an increase in OUD treatment drugs post-MA-PDMP. In combination with our main finding of a decrease in opioid prescribing, the associational increase in OUD MAT prescribing post-implementation of MA-PDMPs may be evidence of provider recognition of misuse among Primary Care, Internal Medicine, and Emergency Medicine patients. However, additional research is needed to evaluate the prescribing behavior of OUD treatment drugs.

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

[14] Group refers to the individual datasets created prior to stacking.

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 and 61-percent of these prescribers reduce the number 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. Morever, our results suggest that MA-PDMPs may even aid in combating the opioid epidemic by leading to an increase in the prescribing of OUD treatment drugs. Overall our findings may indicate that MA-PDMPs are moving certain providers toward more appropriate prescribing of pain medications [Bao et al. (2016)]

Moreover, the benefits of the mandate have become increasingly clear. MA-PDMPs have been found to reduce utilizing multiple providers for opioid prescriptions [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 shows that MA-PDMPs yield additional benefits when 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 states where a query is voluntary [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 or consider technological advances that may improve PDMP use [Weiner et al. (2021)]. 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.

There are some limitations of our study. First, the enactment and implementation of MA-PDMPs largely occurred when many states were also implementing other programs to combat the opioid epidemic (e.g., DEA crackdowns on pill mills and broad CDC guidance on proper opioid prescribing). To the extent that any of these other programs, interventions, or guidelines are associated with the implementation of MA-PDMPS, these results would describe associations and not causal effects. While sensitivity analyses consider several other programs like prescription limit laws, pain clinic laws, and exceptions to mandatory access queries, other important programs and interventions should be considered. We also cannot observe whether MA-PDMP legislation is passed in conjunction with other educational initiatives or lead to other

specialty-specific guidelines. However, given that the opioid epidemic is a nationwide phenomenon, it is reasonable to assume that these initiatives and procedures are recommended across states regardless of MA-PDMP status. Second, there are two data limitations related to our primary data source. CMS Part D public use files do not document providers practicing in multiple states at the same time. The state location from CMS indicates the "primary" practice location. If a provider has medical licensing in multiple states and is registered with the DEA to prescribe controlled substances in multiple states, we are unable to detect this in the public use files. However, according to the Biennial Census of Actively Licensed Physicians in 2010 and 2018, over 78 percent of licensed providers have only one active state medical license. In addition, morphine milligram equivalents (MMEs) are not available in Part D PUFs, as they are in the Medicare claims data, to determine if providers switched to more or less potent opioids or to see if they adjusted milligram amounts. Prior studies have found that MA-PDMPs are not associated with changes in opioid dosing [(Deyo et al., 2018; Chang et al., 2016)]. Although not as informative as MMEs, we examine the effect of MA-PDMPs on the number of days supplied and find similar results. Third, when studying the association between MA-PDMP implementation and opioid use disorder medication-assisted treatment and opioid overdose reversal drugs, we do not control the number of buprenorphine-waivered providers. However, between 2010 and 2016, the number of new waivers increased only slightly from 2,000 to roughly 4,500 nationally (Grimm, 2020). Additionally, the majority of waivered providers treat fewer than 30 patients at one time (Grimm, 2020). It is unlikely that increases in buprenorphine waivers drive the association between MA-PDMPs and prescribing for opioid use disorder or opioid overdose reversal.

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 its propensity to prescribe opioids is essential to combating this national emergency.

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A Appendix

A.1 Opioid policy documentation and detail

Table A1: MA-PDMP Implementation Month, Year

(a) States A-K

State	Year	Month
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		

(b) States K-N

State	Year	Month
KY	2012	7
LA ††	2008	1
MA	2014	7
MD †	2018	7
ME		
MI		
MN	2017	1
MO		
MS		
MT		
NC		
ND		
NE		
NH	2016	1
NJ	2015	11
NM	2012	9
NV ††	2007	10

(c) States N-Z

State	Year	Month
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 †	2018	1
WV	2012	6
WY		

Notes. MA-PDMP implementation timing acquired from http://www.pdmpassist.org and http://www.pdaps.org/.
† denotes states included in our control because MA-PDMP implemented after study period
†† denotes states omitted from analyses because MA-PDMP implemented prior to study period
⋆ denotes states omitted from analyses because 6 months or less of post-implementation data available.

Table A2: Association between Provider Unobserved Status and MA-PDMP Treatment

Dependent Variable: Binary equal to one if provider i is unobserved in year t

Variable	(1) Primary Care	(2) Internal Medicine	(3) Emergency Medicine	(4) Surgery	(5) Palliative Care & Oncology	(6) Pain Medicine
Post-MA-PDMP$_{st}$	0.014*	0.006	0.019	-0.010	-0.016	-0.022
	(0.008)	(0.008)	(0.022)	(0.014)	(0.018)	(0.014)
R-squared	0.489	0.515	0.456	0.493	0.458	0.530
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Provider fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	806,331	677,719	316,958	508,982	106,117	28,628
Providers	106,067	89,930	42,351	66,081	14,378	4,590

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. Standard errors are given in parentheses and clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Number of days supplied of opioid drugs per provider

Specialty	Mean	Std Dev	Min	Max
Primary Care	5,756.4	8,896.2	11	332,975
Internal Medicine	5707.2	8968.6	11	427,554
Emergency Medicine	550.0	3193.7	11	260,304
Surgery	2308.4	10929.9	12	577,526
Palliative care & Oncology	1,886.6	2,800.7	15	102,594
Pain Medicine	31,344.0	44,342.1	39	537,339
Total	4303.1	10798.4	11	679,208

Table A4: Prescription Limit Laws

State	Limit Law Implementation Year	Limit Law Implementation Month	Number of Days Limited	Other Limits 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		lowest effective dose
ME	2017	1	7	
MI				
MN	2017	7	4	
MO	1988	12	30	
MS				
MT				
NC	2018	1	5	
ND				
NE				
NH	2017	1	7	lowest effective dose
NJ	2017	5	5	lowest effective dose
NM				
NV	2017	6	14	90 MME per day
NY	2016	7	7	
OH	2017	8	7	30 MME per day
OK				
OR				
PA	2017	1	7	
RI	2017	3	20	30 MME per day
SC	2007	6	31	
SD				
TN	2013	10	30	
TX				
UT	2017	3	7	
VA	2017	3	7	
VT	2017	7	7	varies by pain level
WA				
WI				
WV				
WY				

A.1.1 MA-PDMP exemptions

As of 2021, many states MA-PDMP statutes and codes contain exemptions for certain medical situations or for patients with particular medical conditions. Many exemptions are patient-specific or days-supplied-specific. Since our data is not granular enough to detect these circumstances, we focused on exemption statutes that would apply across all patients for a given type of provider.

The language that provides these exemptions varies. Sometimes, it is quite straight forward as in OH Admin Codes 4731-11-11 to -14: (11) Standards and procedures for review of "Ohio Automated Rx Reporting System" (OARRS):

> (G) A physician shall not be required to review and assess an OARRS report when prescribing or personally furnishing an opioid analgesic, benzodiazepine, or other reported drug under the following circumstances, unless a physician believes or has reason to believe that a patient may be abusing or diverting reported drugs: (1) The reported drug is prescribed or personally furnished to a hospice patient in a hospice care program as those terms are defined in section 3712.01 of the Revised Code, or any other patient diagnosed as terminally ill; (2) The reported drug is prescribed for administration in a hospital, nursing home, or residential care facility; (3) The reported drug is prescribed or personally furnished in an amount indicated for a period not to exceed seven days; (4) The reported drug is prescribed or personally furnished for the treatment of cancer or another condition associated with cancer; and (5) The reported drug is prescribed or personally furnished to treat acute pain resulting from a surgical or other invasive procedure or a delivery.

In other cases, the statutes may/may not apply in some cases for providers, but additional information on medical encounters would be required to assess whether or not the exemption applies. For example, AK's statute (AK Statute §17.30.200) reads that a prescribers must review information in the PDMP before prescribing or administering a schedule II or III substance, but prescribers are exempt from this requirement when a person is "receiving treatment (i) in an inpatient setting; (ii) at the scene of an emergency or in an ambulance...; (iii) in an emergency room; (iv) immediately before, during, or within the first 48 hours after surgery or a medical procedure; (v) in a hospice or nursing home that has an in-house pharmacy" or the prescription is non-refillable in a quantity intended to last for no more than 3 days. These exemptions do not broadly apply to all of a provider's prescribing, but rather specific circumstances of care that are not observed in our data. As an additional example, KY's statute (KRS 218A.172 & 218A.205) states that

regulations may exempt those prescribing "immediately prior to, during, or within the fourteen (14) days following an operative or invasive procedure or a delivery if the prescribing or administering is medically related to the operative or invasive procedure or the delivery and the medication usage does not extend beyond the fourteen (14) days or to treat a patient in an emergency situation." These policies may exempt surgical or emergency medicine providers in some circumstances, but potentially not all. They may play a role in why large, significant changes are not observed following MA-PDMP implementation among Emergency Medicine and Surgery providers in addition to the fact that there are often not viable opioid substitutes for pain treatment in many of the circumstances that are exempt.

Table A5: MA-PDMP Palliative care & Oncology exemptions

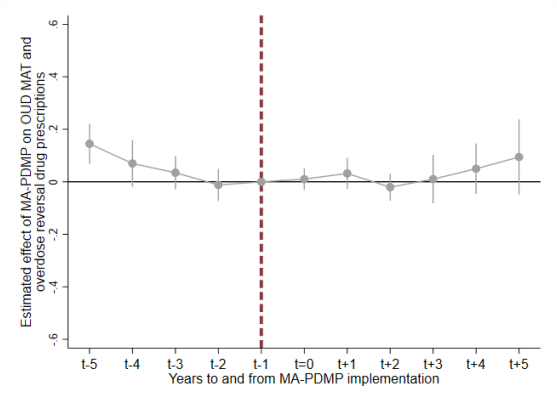
State	MA-PDMP Year	Any Exemptions	Providers exempted	Year exemptions implemented	Month exemptions implemented	Statute / Code
AL						
AK	2017	No				AK Statute §17.30.200
AZ	2017	Yes	Both	2017	10	AZ Rev Statute §§36-2601 to 2611
AR	2017	Yes	Palliative Care	2017	1	AR Code § 20-7-604 (2017)
CA	2018	Yes	Palliative Care	2020	1	CA HSC §11165.4
CO						
CT	2015	No				Public Act 15-198, CT Gen Statute §§21a-254
DE	2012	No				DE Code Title 16 §4798
DC						
FL						section 893.055(8), Florida Statutes
GA	2014	No				GA Code §§16-13-65
HI						
ID						
IL	2018	Yes	Both	2018	1	Public Act 100-0564 Section 5.314.5
IN	2014	No				IN Code § 35-48-7-11.1
IA						
KS						
KY	2012	Yes	Both	2013	3	KRS 218A.172 & 218A.205
LA	2008	Yes	Both	2016	5	LA Rev Statute §§40:978
ME						
MD	2018	Yes	Both	2018	7	MD Health-Gen Code § 21-2A-04.2
MA	2014	No				105 Mass. Reg. 700.012(G)
MI						
MN	2017	Yes	Both	2021	1	MN Statute Sect. 152.126 Subd. 6.
MS						
MO						
MT						
NE						
NV	2007	Yes	Both	2019	7	NV Rev Statute §§639.23507, AB 239 Exemptions
NH	2016	No				NH Statute §§318-B:31-38
NJ	2015	No				NJ Statute §§24:21-54
NM	2012	No				NM Statute §30-31-16
NY	2013	No				NY Code Regs Title 10 §§ 80.63
NC						

Note. In Arkansas, Oncology has very limited exemptions for patients with malignant cancer. PDMP query is still required but less frequently.

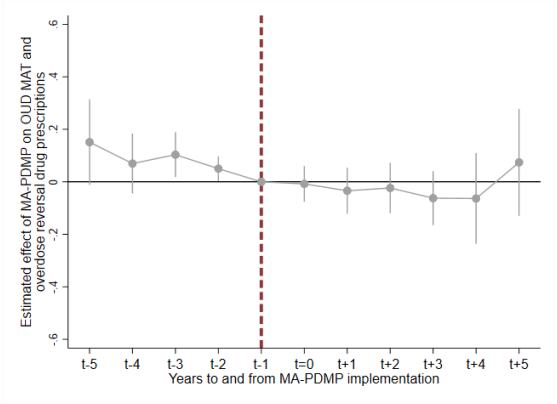
Table A3: MA-PDMP Palliative care & Oncology exemptions, continued

State	MA-PDMP Year	Any Exemptions	Providers exempted	Year exemptions implemented	Month exemptions implemented	Statute / Code
ND						
OH	2012	Yes	Both	2011	12	OH Admin Code §§4731-11-11 to -14
OK	2011	Yes	Palliative Care	2015	11	63 OK Stat § 63-2-309Dv1
OR						
PA	2017	No				PA ABC-MAP Act of Oct 27. 2014 (Revised 2017) P.L. 2911 No. 191
RI	2016	No				RI Gen Laws §21-28-3.18
SC	2017	No				S.C. Code Ann. § 44-53-1645
SD						
TN	2013	No				TN Code §§53-10-310
TX	2019	No				TX Admin Code 22.9.170.C§170.9
UT	2017	No				UT Code §§58-37f-101 to 801
VT	2015	No				18 V.S.A. § 4289
VA	2015	Yes	Palliative Care	2016	7	VA Code § 54.1-2522.1
WA						
WV	2012	No				WV Code §§60A-9-5a
WI	2018	Yes	Palliative Care	2018	1	Wisconsin CSB 4.105
WY						

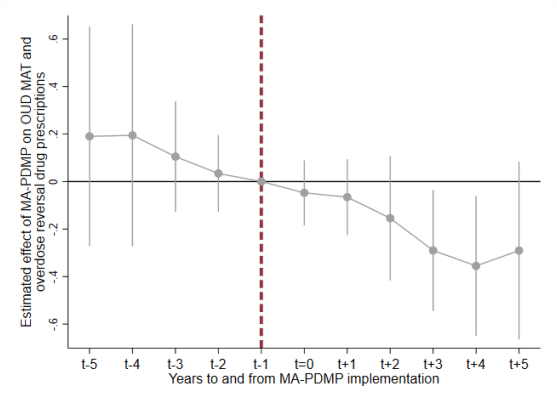
Figure A1: Event studies, OUD MAT and opioid overdose reversal drug prescribing at the intensive margin



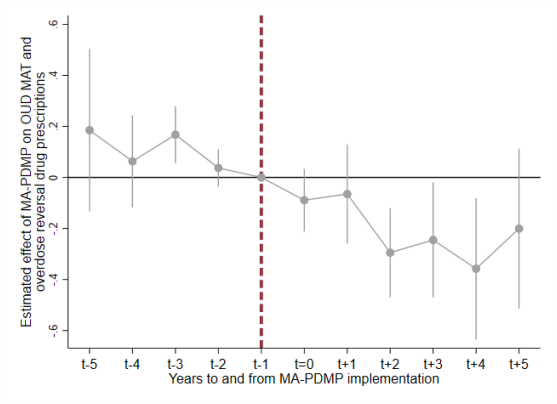
(a) Primary Care



(b) Internal Medicine



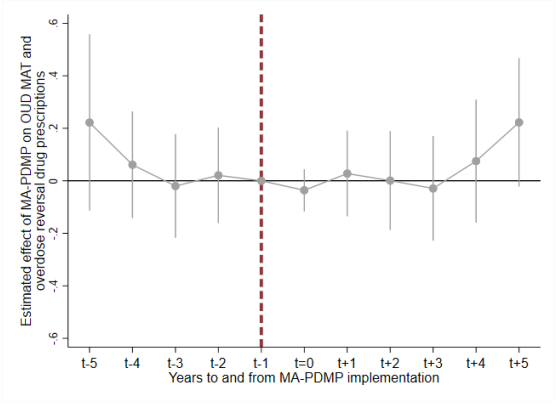
(c) Emergency Medicine



(d) Surgery

Not examined due to small sample size problems.

(e) Palliative Care and Oncology



(f) Pain Medicine

Note. The y-axis plots coefficient estimates and 95 percent confidence intervals from equations (1 and 3) from a Poisson regression of OUD MAT and opioid overdose reversal prescriptions on indicators with years to and since MA-PDMP implementation with state and year fixed effects. Data are provider-year level and the study period is 2010-2017.

A.2 Sensitivity analyses

A.2.1 Adjusting for both provider- and state-level serial correlation

It is possible that serial correlation is present both at the level of policy implementation (state) and at the level of opioid prescribing (provider). High-dimensional fixed effects model implementation (ppmlhdfe) permits multi-way clustering. Therefore, we assess the robustness of our results to adjusting for two-way clustering at the provider- and state-level. Our findings are robust to this adjustment, and confidence intervals are unaffected. Since providers are nested within states and relocation is uncommon (less than 2 percent of providers in our sample), provider-clustering is largely nested within state-level clustering already.

A.2.2 Adjusting for covariates

In this sensitivity analysis, we include state-level covariates documented in existing literature as being associated with opioid prescribing, opioid overdose hospitalizations, and opioid overdose death including the unemployment rate [Hollingsworth et al. (2017)], the poverty rate [Ghertner and Groves (2018)], the number of total medicare enrollees (standard and Medicare Advantage) in state s and year t [Powell et al. (2020), and the passage of medical marijuana laws [Bradford and Bradford (2018)]. Table A4 provides summary statistics for continuous state-level control variables included in this sensitivity analysis.

Our results are largely robust to the inclusion of state-level demographic information and the passage of medical marijuana laws, but the adjustment for these covariates does reduce the significance level of MA-PDMP implementation in Years 4+ from 5 percent to 10 percent among Emergency Medicine providers.

Table A4: Summary statistics for state-level demographic covariates

Variable	Mean	Std Dev	Min	Max
Unemployment rate	6.75	2.16	2.40	12.60
Poverty rate	13.94	2.77	6.40	22.70
Medicare enrollment (in thousands)	2,140.80	1,551.43	64.03	5,915.87

A.2.3 Including only providers observed in all years

A challenge due to CMS privacy rules is that we cannot always observe every provider for the entirety of the sample period. If this data is not missing at random, this may bias our results. In Section 4.1, 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" and "moving

out" of our dataset because of MA-PDMP implementation. We complement this analysis by restricting our main specification to providers we observe in every year of the study, i.e. creating a balanced panel of longitudinally observed providers. Our main results are robust to this sensitivity analysis.

A.2.4 Including only most commonly prescribed opioids

Given that some opioids are vastly more popular than others, it is of interest to see if our results are consistent among only the most commonly prescribed 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 where the outcome, the number of opioid prescriptions, includes only those classified as hydrocodone, oxycodone, or tramadol. Our main findings are robust to this restriction, except for Emergency Medicine providers Years 4+. The long-term impact of MA-PDMP implementation is much less precisely estimated in this sensitivity analysis.

A.2.5 Adjusting for composition of opioids prescribed by type

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 providers and opioid drugs, we implement an alternate specification accounting for the percent of each provider's opioid prescribing in each year in five opioid type classifications: hydrocodone, oxycodone, tramadol, morphine, and codeine. Results from this specification are are consistent with our main findings.

A.2.6 Adjusting for truncation to protect beneficiary privacy

As described previously, when a prescriber has 10 or fewer prescriptions for any given drug in any given year, the provider-drug record is excluded from PUFs to protect the privacy of Medicare beneficiaries. This means data on our outcome of interest, opioid prescribing, is truncated. It is well documented that results can be notably biased when dependent variable truncation is ignored [Greene (2011); Greene (2008); Long (1997)]. Therefore, we apply the following estimation strategy to our provider-level data to adjust estimates for CMS privacy regulations. In the Part D PUFs, we observe provider i prescribing of opioid drug j in state s in year t, Y_{ijst}, conditional on $Y_{ijst} > 10$ − the truncation point of the CMS Part D PUFs. Therefore,

provider i's aggregate prescribing behavior for all opioid drugs $j = 1, ..., J$ can be given by

$$E\Big[Y_{ist}|Y_{ist} > 10 * \sum_{j=1}^{J} I[Y_{ijst} > 10]\Big] = \exp\Big(\mathbf{W}_{ist}\Big) \tag{5}$$

where $\sum_{j=1}^{J} I[Y_{ijst} > 10]$ is the number of opioid drugs prescribed by provider i in state s year t. That is, we set the truncation level separately for each provider as the number of opioid drugs they prescribe in each year multiplied by the drug-level truncation point of 10. We then estimate this model using truncated Poisson models. Our results are also robust to this alternative specification.

Note that this aggregate provider-level truncation point may contain measurement error. For example, suppose a provider prescribes 5 opioid drugs that are observed in the PUFs in a given year. This approach would set this provider's truncation point for this year at 50. There are many other opioid drugs that could have been prescribed and not observed. It is possible that this provider writes one prescription for another 100 opioid drugs, which would make the proxy truncation point we use inaccurate by 50. It is also possible that the provider writes 5 prescriptions for 100 opioid drugs which would make our proxy truncation point inaccurate by 450. Unfortunately, it is impossible to know how inaccurate this proxy truncation point is.[15] Therefore, we also run specifications using provider-drug-level data where we can accurately specify the truncation point at 10 on drug-level data. Unfortunately, it is not possible to simultaneously account for accurate drug-level truncation *and* account for provider-level unobserved hetereogeneity (fixed effects) in these sensitivity analyses. The draw-back of using Truncated Poisson estimation in Stata is that it does not difference out provider-level unobserved heterogeneity, and it not computationally feasible to directly include provider-level fixed effects because of the large number of providers. These specifications are given by

$$E\Big[Y_{ist}|Y_{ijst} > 10\Big] = \exp\Big(\gamma_s + \theta_t + \lambda_j + \beta \text{Post-MA-PDMP}_{st}\Big) \tag{6}$$

Results from this sensitivity analysis are presented in Table A5, and our qualitatively similar to our results from Table 2. Because of our inability to simultaneously account for provider-level unobserved hetereogeneity and drug-level truncation, it is difficult to state the reliability and accuracy of this sensitivity analysis since provider-level unobserved hetereogeneity is almost certainly present.

[15] CMS lists of opioid drugs for this data include around 100 drugs in each year from 2013-2017.

Table A5: MA-PDMP Effect after in drug-level data and accounting for truncation

Variable	(1) Primary Care	(2) Internal Medicine	(3) Emergency Medicine	(4) Surgery	(5) Palliative Care & Oncology	(6) Pain Medicine
Panel A: Original Estimates, Table 2						
MA-PDMP-Years0-3$_{st}$	-0.046***	-0.043**	-0.041	-0.038	-0.012	-0.037
	(0.016)	(0.018)	(0.031)	(0.033)	(0.028)	(0.032)
MA-PDMP-Years≥4$_{st}$	-0.094**	-0.102***	-0.102**	-0.069	-0.048	-0.129*
	(0.037)	(0.039)	(0.043)	(0.081)	(0.050)	(0.077)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Provider fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	597,296	469,752	220,387	346,541	71,439	22,848
Providers	106,067	89,930	42,351	66,081	14,378	4,590
Panel B: Drug-level data adjusted for truncation of drug j at 10 prescriptions or less						
MA-PDMP-Years0-3$_{st}$	-0.018	-0.018	-0.023	-0.026	0.036*	-0.011
	(0.012)	(0.016)	(0.019)	(0.025)	(0.020)	(0.042)
MA-PDMP-Years≥4$_{st}$	-0.045*	-0.049	-0.091***	-0.039	0.034	-0.099
	(0.026)	(0.038)	(0.035)	(0.069)	(0.043)	(0.078)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Provider fixed effects	No	No	No	No	No	No
N	2,353,719	1,840,835	383,801	799,258	223,907	198,554
Providers	106,067	89,930	42,351	66,081	14,378	4,590

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 Panel A is Poisson regression, and the estimation technique employd in Panel B is Truncated Poisson regression. Standard errors are given in parentheses and clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Data Appendix

B.1 Sources

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. The Part D PUFs are **not** Medicare beneficiary claims data as used in Buchmueller and Carey (2018) and other work. The public use files are aggregated summary files at the provider-drug-year level that are adjusted to protect both beneficiary and provider privacy. The advantage of using these files is that they are free to researchers and publicly available, but they do not contain the level of detail of claims data that can be purchased. 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. In 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 throughout the United States for a total of 9,451,120 provider-drug-year level observations. For each prescriber and drug, the dataset includes the total number of prescriptions that were dispensed, which include original prescriptions and any refills. To protect the privacy of Medicare beneficiaries, any aggregated records derived from 10 or fewer claims are excluded from the Part D Prescriber PUF.

B.2 Specialties

The specialties considered in our anlayses (Primary Care providers, Internal Medicine, Emergency Medicine, Surgery, Palliative care & Oncology, and Pain Medicine) and their corresponding listings are provided in Table B1. We did not analyze providers from the CMS data who specialize in other areas of medicine, those who are other types of healthcare providers like dentists, physician assistants and nurse practitioners, or those who are not licensed to prescribe opioid medications. These omitted provider specialties are listed in Table B2.

Table B1: Specialty Groupings

Provider Group	CMS Recorded Specialties
Primary Care	Family Medicine
	Family Practice
	General Practice
	Geriatric Medicine
	Pediatric Medicine
	Preventive Medicine
	Pediatrics
	Osteopathic Manipulative Medicine
Internal Medicine	Internal Medicine
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
Palliative Care and Oncology	Hospice and Palliative Care
	Gynecological/Oncology
	Hematology/Oncology
	Medical Oncology
	Radiation Oncology
	Gynecological Oncology
	Hematology-Oncology
Pain Management	Pain Management
	Interventional Pain Management

Table B2: Specialties omitted from all analyses

Provider Group	CMS Recorded Specialties
Specialists	Diagnostic Radiology
	Interventional Radiology
	Nuclear Medicine
	Radiology
	Radiologic Technologist
	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
	Hospitalist
	Interventional Cardiology
	Critical Care (Intensivists)
	Geriatric Psychiatry
	Neuropsychiatry
	Psychiatry
	Psychiatry & Neurology
	Psychologist (billing independently)

continued on next page

Table B2: Specialties omitted from all analyses, continued

Provider Group	CMS Recorded Specialties
Specialists, continued	Clinical Neuropsychologist
	Clinical Psychologist
	Psychologist
	Psychologist, Clinical
	Psychoanalyst
	Behavioral Analyst
	Developmental Therapist
	Marriage & Family Therapist
	Addiction Medicine
	Rehabilitation Agency
	Rehabilitation Practitioner
	Rehabilitation Counselor
	Physical Medicine & Rehabilitation
	Physical Medicine and Rehabilitation
	Sports Medicine
	Neuromusculoskeletal Medicine, Sports M
	Neuromusculoskeletal Medicine, Sports Medicine
	Physical Therapist
	Physical Therapist in Private Practice
	Physical Therapy Assistant
	Occupational Therapy Assistant
	Occupational therapist

Table B2: Specialties omitted from all analyses, non-physicians

Provider Group	CMS Recorded Specialties
Dentist	Dentist
	Dental Assistant
	Dental Hygienist
	Denturist
	Oral Surgery (Dentists only)
	Oral Surgery (Dentists only)
	Oral Surgery (dentists only)
Mid-Level Provider	Nurse Practitioner
	Physician Assistant
	Certified Clinical Nurse Specialist
	CRNA
	Certified Registered Nurse Anesthetist (CRNA)
Organizational NPIs	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

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Table B2: Specialties omitted from all analyses, non-physicians, continued

Provider Group	CMS Recorded Specialties
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
Non-Prescribers	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

B.3 Opioid Drugs

Table B3: 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

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Table B3: 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

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Table B3: 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

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Table B3: 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

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Table B3: 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

Table B4: Medicare Part D Prescription Frequency for Opioids by Type

Drug Type	Frequency	Percent	Cum. Freq.
butorphanol	226,519	0.05	0.05
codeine	14,744,315	3.38	3.43
difenoxin	98	0.00	3.43
dihydrocodeine	10,243	0.00	3.43
diphenoxylate	3,554,476	0.81	4.25
fentanyl	17,448,253	4.00	8.25
hydrocodone	196,626,070	45.06	53.30
hydromorphone	4,962,179	1.14	54.44
levorphanol	12,893	0.00	54.44
meperidine	129,118	0.03	54.47
morphine	21,369,001	4.90	59.37
opium	5,519	0.00	59.37
oxycodone	92,555,748	21.21	80.58
oxymorphone	1,691,789	0.39	80.97
pentazocine	38,035	0.01	80.98
sufentanil	24	0.00	80.98
tapentadol	453,384	0.10	81.08
tramadol	82,562,208	18.92	100.00
Total	436,389,872	100.00	100.00