NBER WORKING PAPER SERIES

HOW DO OPIOID PRESCRIBING RESTRICTIONS AFFECT PHARMACEUTICAL PROMOTION? LESSONS FROM THE MANDATORY ACCESS PRESCRIPTION DRUG MONITORING PROGRAMS

Thuy D. Nguyen
W. David Bradford
Kosali I. Simon

Working Paper 26356
http://www.nber.org/papers/w26356

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2019

This research was supported in part by funding from Indiana University's Grand Challenge Initiatives. We acknowledge the Indiana University Pervasive Technology Institute for providing high-performance-computing resources that have contributed to the research results reported in this paper (https://pti.iu.edu). We thank Jeanette Samyn and Cong Gian for assistance with proofreading. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

How do Opioid Prescribing Restrictions Affect Pharmaceutical Promotion? Lessons from the Mandatory Access Prescription Drug Monitoring Programs

Thuy D. Nguyen, W. David Bradford, and Kosali I. Simon

NBER Working Paper No. 26356
October 2019
JEL No. I11,I18

ABSTRACT

Prior work considers effects of prescribing restrictions on opioid use but not upstream implications for pharmaceutical marketing activities, despite the inordinate role many believe marketing played in the crisis. Our study proposes a stylized model of pharmaceutical payments and investigates the impact of Mandatory Access Prescription Drug Monitoring Programs (MPDMPs) on opioid-specific commercial promotion directed at physicians. We find that MPDMPs reduce promotion on both extensive and intensive margins. Our results are consistent with economic theory, predicting lower promotional activities when return on investment decreases after state prescribing restrictions, and indicative of MPDMPs' role in affecting opioid use through reduced promotion.

Thuy D. Nguyen
O'Neill School of Public
and Environmental Affairs
Indiana University
Bloomington, IN 47401
thdnguye@indiana.edu

W. David Bradford
201C Baldwin Hall
Department of Public Administration
& Policy
University of Georgia
Athens, GA 30602
bradfowd@uga.edu

Kosali I. Simon
O'Neill School of Public and
Environmental Affairs Indiana University
Rm 357
1315 East Tenth Street
Bloomington, IN 47405-1701
and NBER
simonkos@indiana.edu

I. Introduction

The abrupt onset of considerably high rates of opioid-related mortality, which continued to increase nationally through 2017, is considered a direct result of important supply-side developments in the US, including aggressive promotional campaigns by opioid pharmaceutical companies (Van Zee, 2009), the introduction of reformulated Oxycontin as well as regulatory restrictions on prescribing (Alpert et al., 2018; Evans et al., 2019). While prescriptions for opioid medications peaked at 260 million in 2012 and fell to around 228 million by 2015 (Chai et al., 2018), opioid mortality rates continued to increase past this point; according to preliminary data from the Centers for Disease Control and Prevention (CDC), 2018 was the first year in which opioid mortality appears to have dropped, by 5.1% (Ahmad et al., 2019).

A set of central policies aimed at reducing opioid abuse, Prescription Drug Monitoring Programs (PDMPs), are operated by individual states and are established to collect data on opioid prescriptions and facilitate the sharing of this data between providers and institutions (Buchmueller and Carey, 2018; Pacula et al., 2018). Several studies have found no differences in opioid-related mortality or abuse rates associated with PDMPs (Paulozzi et al., 2011; Radakrishnan, 2013), though other studies that distinguish between PDMP strengths find that Mandatory Prescription Drug Monitoring Programs (MPDMPs) reduce opioid prescribing and misuse, while voluntary PDMP types do not (Wen et al., 2017; Buchmueller and Carey, 2018; Meinhofer, 2018). Buchmueller and Carey (2018) provide evidence that MPDMPs significantly reduced the percentage of Medicare Part D enrollees obtaining opioid prescriptions from five or more prescribers by 8% in 2007-2013. Wen et al. (2017) show that MPDMPs were also associated with a reduction of 9-10% in Schedule II opioid prescription volume and spending in Medicaid.

Recent studies have investigated unintended consequences of MPDMPs including increases in crime and heroin use (Mallatt, 2018; Dave et al., 2018) and reductions in opioid prescriptions to new patients (Sacks et al., 2019). No prior work has studied its effects

on opioid-related pharmaceutical promotion although MPDMP laws might significantly reduce the rate of return on detailing and lead companies to target less promotion at physicians. On the other hand, these laws could also shift the composition of activities such that companies now target only physicians who are heavy prescribers, for whom PDMPs may impose lower marginal transactional costs. Little is known about the effect of supply-side prescription policies on drug detailing activities of opioid manufacturers, despite large public policy interest in the role of promotion in the current opioid crisis.

We contribute to the literature on economics of pharmaceutical advertising by presenting evidence on the impact of MPDMP laws on opioid-related pharmaceutical promotion to US physicians, showing that laws lead to reductions in overall provider-directed payments (hereafter simplified as opioid detailing). Drug detailing refers to the unique performance - part sales pitch and part educational service - in which pharmaceutical sales representatives present physicians with prescribing information (Greene, 2004).There are two main theoretical views about the general impacts of advertising, of which detailing is a specific type. Robinson (1933) discusses how advertising increases demand for a particular product in the context of a monopolistically competitive market; therefore it leads to increased prices and reduced social welfare. On the other hand, advertising notifies consumers of a product's existence, prices, or other qualities; thereby advertising tends to increase social welfare via reduced search costs and increased competition. Several studies have attempted to examine the roles of pharmaceutical marketing efforts in explaining drug sales, market shares, and prescribing decisions (Stigler, 1961). Berndt et al. (1996) employ IMS America sales and marketing data on the U.S. antiulcer drug market and find that both sales and market-share level are positively and substantially related to minutes of detailing. Despite its role in providing medical information to physicians, Gonul et al. (2001) suggest that drug detailing positively affects prescription choices, although this effect is diminishing. Lakdawalla et al. (2013) studied the theoretical and empirical effects of prescription drug insurance programs on aggregate advertising expenditure for the top 1000 drugs. The authors found that Medicare Part D led to a 14-19% increase in total ad-

vertising spending (including direct to consumer advertising and physician advertising), mainly concentrated in drugs with low price elasticity of demand.

In our study, we extract all opioid-related, direct-to-physician promotional activities from 2014 to 2017 from the Sunshine Act's Open Payments data. We perform fuzzy matching to link the Open Payments data with the National Plan and Provider Enumeration System (NPPES) and Part D Prescriber Public Use File from the Centers for Medicare & Medicaid Services Center in order to collect physician-level characteristics such as gender, years of experience, and opioid prescription volume in the base year, 2013. Finally, we use the variation across states in implementing MPDMPs and a difference-in-difference (DD) empirical strategy to investigate the effects of state prescription policy restrictions on promotional activities aimed at physicians.

We propose a conceptual model that explains how physicians' prescribing decisions are affected by "open payment"-type subsidies and how pharmaceutical companies take those physician reaction functions into account when choosing the level of payment. Abstracting away from the industrial organization of both the physician and pharmaceutical market, we assume that both are price takers and focus on the countervailing effects of MPDMPs on pharmaceutical promotion to physicians. This approach is different from the literature on economics of advertising which focus on competition and advertising decisions of firms (Lakdawalla et al., 2013). In particular, Lakdawalla et al. (2013) proposed a model of oligopoly advertising by branded pharmaceutical firms to explain how prescription drug insurance theoretically affects advertising decisions of firms. The price and competition setting in our model allows us to understand the inter-relationship between physician prescribing choices, pharmaceutical company payment choices and state policy. MPDMPs impose both fixed and operating costs on prescribers to log in to the system, to query, to enter new data, and react to existing data. The optimal proportion of the physician's patients who receive a prescription depends on the costs of MPDMPs and "open payment"-type subsidies. Our model predicts that the dollar value of pharmaceutical manufacturer payments to physicians will fall as state MPDMPs become more burdensome, but that

this effect will be less serious for larger physician practices and may even be positive as the number of patients rises.

We next consider plausible channels through which MPDMPs affect the prescribing behavior of physicians and the implication that carries for the return on investment of drug detailing. Our break-even analysis illustrates two possibilities. First, MPDMPs will reduce the number of opioid prescriptions on average by imposing both fixed and operating costs to log in to the system and to query, enter new data and react to existing data. Second, the effect of MPDMPs on physicians is heterogeneous and depends on a prescriber's prescription volume. Because a low-volume prescriber with too few patients demanding opioids may not be willing to bear the fixed costs, he or she may decline to prescribe opioids following an MPDMP. Therefore, our first and main hypothesis regards whether MPDMPs impede opioid detailing. The second hypothesis is that MPDMPs have a weaker effect on drug detailing among high-volume prescribers.

In our empirical analysis of the prescription opioid market, we obtained considerable support for these predictions. First, MPDMPs have a significantly and substantially negative effect on both the extensive margin (whether a physician receives a payment) and the intensive margin of detailing (measured by the dollar amount of payments as well as the frequency of these payments/visits). On average, such programs lead the typical physician to be 0.9% less likely to receive an opioid promotional payment, to receive an 8.1% smaller payment conditional on receipt, and to offer 7.3% fewer detailing visits. We provide reassuring evidence that these results can be interpreted causally. For one, we implement a placebo test by examining the effects of MPDMPs on the most prescribed groups of drugs, including dermatologicals, hypertensives, antidiabetics, and thyroid agents. We find no effects of MPDMPs on detailing efforts in these drug markets where MPDMPs do not create burdensome prescribing barriers on prescribers. The event study analysis suggests there is no violation of the parallel trends assumption in our DD models. The study thus provides the first evidence of the causal effect of MPDMPs on curbing opioid-related detailing.

Second, we provide evidence on the diminishing negative effects of MPDMPs on commercial promotion of opioids among high-volume prescribers. MPDMPs appear to reduce the frequency of detailing visits to top 5% opioid prescribers, compared to the overall 7.3% reduction in this intensive margin of detailing. We also provide evidence on the heterogeneous effects of MPDMPs predicted by our model in terms of physicians' geographic locations; rates of return are lower in less densely populated areas.

Section 2 provides a stylized model of physician prescribing decisions and pharmaceutical manufacturer drug detailing choices. Sections 3 and 4 describe the data and empirical strategies used in this study, respectively. Section 5 presents our empirical results and section 6 provides a concluding discussion.

II. A Simple Model of Pharmaceutical Payments to Prescribers

In order to motivate our empirical analysis below, we present a highly stylized model of physician prescribing decisions and pharmaceutical manufacturer choices regarding the amount of money to be invested in each physician each year.[1] To focus our attention on the inter-relationship between physician prescribing choices, pharmaceutical company payment choices and state policy, we abstract away from the industrial organization of both the physician and pharmaceutical market, and assume they are price takers in

[1]In this paper, we focus on pharmaceutical companies' direct to physician (DTP) marketing through gifts that are subject to Open Payments reporting. We do not model direct to consumer (DTC) marketing decisions for two reasons. First, there is no mandate for pharmaceutical companies to publicly release DTC data as there is for DTP events; however, we do acknowledge that decisions about allocating marketing budgets to DTC efforts would be driven by return on investment considerations similar to those we model here. There is an important distinction between DTC and DTP marketing for our model though: DTP marketing is a direct subsidy to the providers which can serve to overcome the burden associated with complying with PDMP reporting/access requirements; this is not true for DTC marketing, where if anything higher DTC spending will impose greater costs on providers who must then counsel patients about drugs they have seen advertised. These are sufficiently distinctive incentives that we will not attempt to model both DTP and DTC marketing, though we acknowledge that they may be correlated.

their respective output markets.[2] These assumptions permit us to make progress on the primary question at hand: How are physicians' prescribing decisions affected by "open payment"-type subsidies? And, how do pharmaceutical companies take those physician reaction functions into account when choosing the level of payment? In particular we focus on the countervailing (though, potentially reinforcing) effects of MPDMPs and pharmaceutical promotion to physicians.

We assume that a single pharmaceutical company manufactures a single prescription drug that may be subject to new MPDMP oversight. The drug is the only one in the market, and so the representative physician must choose the proportion of her patients to whom she will write a prescription. The MPDMP oversight for the drug in question will vary in its intensity, thus varying the costs that it imposes on the physician for prescribing each unit of the controlled drug. In general, if MPDMP access and filing requirements impose additional marginal costs on the physician for prescribing the drug, she will prescribe less of it, *ceteris paribus*. The pharmaceutical company can counter this by giving the physician payments that are an increasing function of the proportion of visits for which she writes a prescription.[3]

The theoretical framework is simple: the pharmaceutical company sets the promotional rules by choosing a payment function that depends on prescription intensity; given this payment schedule, physicians choose what proportion of their patients will receive a prescription. Since we assume pharmaceutical company profits are a linear sum of the profits flowing from each individual physician, with no strategic interdependence between the physicians, analysis of the problem is reduced to the choices of the pharmaceutical company and a representative physician. We obtain the solution via backward induction.

[2]The objective functions in the model that follows could be easily extended to assume price setting on the part of the manufacturer, or even visit price setting on the part of physicians, with some assumptions about patient demand. These models add non-trivial complexity to the solutions, but without contributing substantially to our understanding of the fundamental question at hand. Thus, fully exploring models with supply side market power will be left for future research.

[3]While it would clearly be a violation of federal and state anti-kickback laws for pharmaceutical companies to *explicitly* tie payments to prescriptions, they may implicitly do so by granting larger payments to physicians who historically prescribe more. Theoretically, we will make this association explicit.

A. The physician's base choice

Assume that a representative physician has a constant flow of N patients who each demands one visit. For this simplest model, we further assume that patients are fully insured on the margin, and so the quantity flow of patients N does not respond to the unit visit price or the cost of any prescribed medication. Thus, each physician will receive a net reimbursement of R for each visit – irrespective of whether a prescription is provided – that represents a unit price net of the marginal cost of production of an office visit.[4] For each visit, the physician can choose whether to provide a prescription to the patient for the single drug that is subject to oversight from a MPDMP – an opioid, for example.

We assume that patients have a condition that may be treated by this pharmaceutical product with some maximum observable clinical treatment effect, G for the patient with the best clinical match. Each use of the drug is also associated with the potential that a patient may incur some iatrogenic harm from the prescription, which is lowest at H, for the patient with the best therapeutic match, and which increases as match quality decreases. For example, a patient using a prescription opioid may benefit from reduced pain and improved mobility; she may also simultaneously risk addiction and subsequent morbidity or mortality associated with opioid abuse. Patients' benefit and harm is characterized by a parameter, θ, which ranges from 0 to 1, where $\theta = 0$ corresponds to the maximum clinical benefit and lowest iatrogenic harm, whereas $\theta = 1$ corresponds to the reverse. If we assume for the sake of simplicity that the benefit and harm functions (g and h) are linear in θ, with intercepts G and H and slopes γ and λ :

$$g(\theta) = G - \gamma\theta, \;\; h(\theta) = H + \lambda\theta \tag{1}$$

[4]Note that this assumption of invariant price, or patient flow, with respect to the outcome of the visit may not be innocuous in our model. If patients are willing to pay more for a visit (or are more likely to seek a visit from the physician) if they get a prescription, then our assumption about constant patient flows and net reimbursement may meaningfully impact the predictions of our model of prescription decisions. Accommodating that potential comes at the cost of substantial notational complexity, and does not obviously improve the model for the purposes of motivating our empirical analysis. Consequently, we leave modeling patient reactions to prescription availability to future research.

then the net clinical benefit, NCB for every patient type would be

$$NCB \equiv g(\theta) - h(\theta) = B - \theta[\gamma + \lambda], \tag{2}$$

such that $B = G - H$ is the maximum possible net clinical benefit.

Further assume that for each physician, patients are ranked along $\theta \in [0, 1]$ from the "best" match for the prescription to the "worst" match, then the value of θ also corresponds to the proportion of the physician's patients who receive a prescription. In that case, recognizing that the patient at $\theta = 0$ enjoys the maximum net clinical benefit of B and that the marginal patient receiving a prescription gets a net clinical benefit of $B - \theta[\gamma + \lambda]$, then given a physician choice of a threshold θ, the average treatment effect on the treated is

$$ATET = B - \frac{1}{2}\theta[\gamma + \lambda]. \tag{3}$$

Assuming that patients are fully insured and facing no out-of-pocket costs for the visit (which each patient gets) or the prescription (which θ proportion of the patients receive), and that patients' demand is independent of θ, then the representative physician facing a flow of N patients will write $[1 - \theta]N$ prescriptions. The physician calculus is therefore to maximize the value function V with respect to θ. V depends on profit from the visit and the physician's preference valuation of average patient health flowing from the prescription, α:

$$\max_{\theta} V = \left[R + \alpha\theta[B - \frac{1}{2}\theta\,[\gamma + \lambda]]\right] N. \tag{4}$$

Clearly N plays no role in the $F.O.C.$ of the representative physician and so will be ignored hereafter, on the assumption that all physicians have the same patient flow. (The implications of this will be discussed below.) If the market had no MPDMP and allowed no pharmaceutical company payments, then the representative physician would choose a threshold value of θ^* such that

$$\alpha B - \alpha\theta[\gamma + \lambda] = 0 \tag{5}$$

or,

$$\theta^* = \frac{B}{[\gamma + \lambda]} \leq 1 \tag{6}$$

Obviously, this is the value of θ^* that maximizes the $ATET$ from Equation (3) – that is, θ^* is associated with the patient where $g(.) = h(.)$.

B. The Physician's Choice with an MPDMP and Pharmaceutical Company Payment

Now assume both that there is an MPDMP in place, and that a pharmaceutical company can seek to mitigate the impact of the MPDMP by giving each representative physician a payment that is increasing in the proportion of patients who receive a prescription. For our purposes, we will assume that all physicians face some form of MPDMP. This is not strictly true for our empirical analysis, in that only 30 states adopted an MPDMP by December 2017. However, as we model it, a state with no MPDMP is the same as a state with an MPDMP that imposes no costs on the resident physicians - and so the model would still apply. We assume that MPDMPs can vary in the costs that they impose on physicians in the state. For example, states with MPDMP laws and/or laws that require daily reporting would be more burdensome than states where the laws explicitly state that physicians do not need to use the MPDMP or that require only weekly reporting. For simplicity, then, we will assume that each physician faces a marginal cost of δ per prescription to comply with the state MPDMP law, where δ is increasing in the strictness of the MPDMP.

At the beginning of the process, the pharmaceutical company sets a payment schedule for each physician that depends on prescribing intensity. Technically (and in a nod to the

reality of anti-kickback statutes) the amount of money that the physician receives from the pharmaceutical company is not a strict (multiplicative) function of the total number of prescriptions, θN, but merely of the proportion of visits that get a prescription. We assume that the company announces a linear payout function, $\omega\theta$, before physicians choose their θ^*. The payment will therefore range from $\omega \cdot 0 = 0$ when no prescriptions are written to a maximum of $\omega \cdot 1 = \omega$ when all patients get prescriptions. Notably, the payment is not tied to patient net clinical benefit in Equation (2) – the pharmaceutical company will be indifferent to whether the patients themselves receive maximum benefit or maximum harm, and so sets a volume-related incentive.

With costs for an MPDMP and pharmaceutical company incentive schedules in place, physicians face the problem:

$$\max_{\theta} V = \left[R + \alpha\theta[B - \frac{1}{2}\theta[\gamma + \lambda]] - \theta\delta \right] N + \omega\theta. \tag{7}$$

Now, the number of patients is a factor in the optimal choice of θ, which is where

$$\alpha B - \alpha\theta[\gamma + \lambda] - \delta + \frac{\omega}{N} = 0. \tag{8}$$

So, with the costs of the MPDMP and pharmaceutical subsidy, the optimal prescribing threshold for the physician becomes

$$\theta^*_{MPDMP} = \frac{\alpha B - \delta + \frac{\omega}{N}}{\alpha[\gamma + \lambda]} \tag{9}$$

Note that if the payment schedule from the pharmaceutical company yields an average payment that is greater than the MPDMP burden then $\theta^*_{MPDMP} > \theta^*$ and more patients receive prescriptions than is optimal. In that circumstance, at least some patients are given prescriptions even though the negative health effects outweigh the positive. As we will see in Section D. below, this will not always be the equilibrium outcome.

C. The Pharmaceutical Company Choice

Equation (9) above represents the reaction function for the representative physician to the pharmaceutical company choice of payment schedule. Assume that the pharmaceutical manufacturer operates in a market where it is a price taker at P per prescription sold, and that it markets its product to K physicians each of which sees N_i patients, where individual patient demand is unresponsive to P or the physician's choice of θ^*. The pharmaceutical company thus chooses a vector of contract terms to

$$\max_{\underline{\omega}} \Pi = \sum_{i=1}^{K} \left[P\theta_i^* N_i - \omega\theta_i^* \right]. \tag{10}$$

Isolating the decision with respect to the i^{th} physician the manufacturer chooses ω_i according to

$$\omega_i^* = \frac{PN_i \frac{\partial \theta_i^*}{\partial \omega_i} - \theta_i^*}{\frac{\partial \theta_i^*}{\partial \omega_i}}. \tag{11}$$

Substituting the definition for θ_i^* from Equation (9) above, we get

$$\omega_i^* = \frac{1}{2} N_i [P - \alpha B + \delta_i] \geq 0, \tag{12}$$

where δ_i is now indexed by the individual physician to allow physicians to experience different levels of MPDMP burden.[5]

Substituting the solution for ω_i^* into Equation (9) yields the optimum solution in terms of the model parameters of

[5]Different states will have different MPDMP terms, which will create variation in δ. Further, physicians may choose institutional structures – *e.g.* adopting electronic medical record systems or relying on nurse practitioners or physician extenders to manage interactions with the MPDMP – that could lower the effective δ they face. We will not explicitly model the potential for this variation in the firm production function to be an avenue for maximizing (7), though we will discuss how such an extension would affect the equilibrium below.

$$\theta^*_{MPDMP} = \frac{B + P - \delta}{2\alpha[\gamma + \lambda]} \tag{13}$$

The optimal ω_i^* chosen by the manufacturer will be increasing in the patient volume of the physician practice and in the marginal cost imposed on the physician by the MPDMP. While this implies more generous payment schedules for larger practices or for states with MPDMPs that are "must access" or require more frequent reporting, it does not necessarily mean that more money flows to the practices as N_i increases or δ_i decreases. This is because changes to both of those parameters not only induce changes in ω_i^* but also in θ_i^*.

D. Determining Open Payments dollars to the physician

Given the simple theoretical framework we propose, the ultimate payment amount, S_i, flowing from the manufacturer to each physician depends on two things: the profit maximizing payment schedule, ω_i^*, set by the manufacturer and the induced prescribing threshold, θ_i^*, set by the physicians. The i^{th} physician will receive a payment from the manufacturer of

$$S_i = \theta_i^* \dot{\omega}_i^* \tag{14}$$

Differentiating (14) with respect to δ_i yields

$$\frac{\partial S_i}{\partial \delta_i} = \omega_i^* \frac{\theta_i^*}{\partial \delta_i} + \theta_i^* \frac{\omega_i^*}{\partial \delta_i}. \tag{15}$$

Differentiating Equations (9) and (12) with respect to δ_i and substituting those terms into (15) yields

$$\frac{\partial S_i}{\partial \delta_i} = \frac{\frac{1}{2}N_i\left[\alpha B - \delta - \frac{\omega_i^*}{N_i}\right]}{\alpha\left[\gamma + \lambda\right]}. \tag{16}$$

So, the effect of the marginal cost of each prescription associated with the MPDMP on the total amount of payment passing from the manufacturer to the physician depends on the sign of the bracketed term in the numerator of (16). If the value that the physician gets from the health accruing to the *best* matched patient from the prescription, B, net of the MPDMP burden δ_i turns out to be less than the per-patient payment received by the physician, $\frac{\omega_i^*}{N_i}$, then stricter (*i.e.*, more burdensome) MPDMPs will actually reduce the total money flowing from manufacturer to physician. Note that $\alpha B - \delta < \frac{\omega_i^*}{N_i}$ will be less likely to be true for larger practices.

The market conditions under which this holds can be seen by substituting the definition of ω_1^* into (16) above. Since $\frac{\partial S_i}{\partial \delta_i} < 0$ only if the bracketed term in the numerator is less than zero, this reduces to the requirement that $\alpha B - \frac{1}{3}P < \delta_i$. This condition will hold for prescription drugs where the market price is high relative to the net clinical benefit from the drug.[6] Under the assumptions of the model the only social value that flows from the drug is the physician's value accruing from patients' improved health (we have abstracted away from the patients' surplus received from their own health). So, the pharmaceutical company will choose to invest more *in total* to doctors in the form of "Open Payment"-type gifts when MPDMPs become more burdensome if the manufacturers drug is of relatively high value, compared to the market price. If the drugs in question are of relatively low value compared to the market price, then as the MPDMP becomes more burdensome the total payments from manufacturers to physicians will fall.

Thus, our simple model has at least three clear predictions: if $\alpha B - \delta < \frac{\omega_i^*}{N_i}$ then the dollar value of pharmaceutical manufacturer payments to physicians will fall as state MPDMPs become more burdensome. This effect will be offset for larger physician prac-

[6] Recall the B corresponds to the intercept for the linear net clinical benefit function, and so represents the highest clinical benefit that the "best matched" patient receives.

tices and may even be positive as N_i rises. And whether total payments per physician rise or fall in the face of increased MPDMP burden depends on whether the drug being subsidized has high or low clinical value relative to its market price.

III. Data and Methods

IV. Data

A. Measures of Opioid-Related Pharmaceutical Promotion

Our dependent variables, derived from the Sunshine Act's Open Payments database for 2014-2017[7], include: 1) an indicator variable for whether a physician received any opioid-related payments; 2) the total dollar amount of payments the prescriber received each year; and 3) the number of times a physician received any payment each year. These measures relate to an equilibrium quantity of opioid detailing received by physicians. Because the distribution of opioid-related payments is heavily right-skewed, the amount of payments and number of times a physician received any payment were logged in the analysis conditional on the receipt of any pharmaceutical promotion.

The Sunshine Act's Open Payments data is publicly released by the Centers for Medicare and Medicaid (CMS). Components of Sunshine Act records include physician name and address, date of payment, a list of up to 5 drugs (or medical devices) that the manufacturer sought to promote with the payment, and a broad classification of what form the payment took. The preponderance of records of payments to physicians in the 2014-2017 database includes the associated drug or device name (for instance, such records accounted for 93.5% of all 2014 payments records).

As in previous studies of pharmaceutical promotion to providers, this study is lim-

[7]Although the Open Payments data exists from 2013 onward, the 2013 data only covers the last 5 months of that year. Thus we begin with 2014 as the first year we observe all direct payments from pharmaceutical companies to physicians for the entire year. We included 2013 data in the quarterly event study analysis in order to expand the interval of the analysis.

ited to non-research and nonequity payments to physicians, referred to as promotional payments (Perlis and Perlis, 2016; DeJong et al., 2016; Hadland et al., 2017). Over the period of 2014 and 2017, research payments from pharmaceutical companies received by physicians amounted to $447.5 million (5.3% of promotional payments); equity payments received amounted to $4.3 billion (50.9% of promotional payments). While other categories of promotional payments may explicitly target prescribing behaviors, research and equity payments do not. Additionally, medical-device-related payments to physicians were excluded, as medication prescribing is the focus of our analysis. Finally, the analysis excluded chiropractors because the primary approach to their practice, chiropractic manipulation, typically does not involve medication.

We used string-based matching to determine all records mentioning at least one opioid prescription drug and extracted these records for analysis. We identified opioid-related payment records using a name list of opioid drugs. Particularly, we constructed the list of prescription opioids by combining the Prescriber Drug Category Lists for opioids from CMS 2014-2017 (CMS, 2018b) and the drug list of narcotic analgesics products from the Ambulatory Care Drug Database System of the Centers for Disease Control and Prevention (CDC, 2018). Alfenta, Alfentanil, Astramorph, and Darvon are some examples of drug names on the CDC list, but not included in the CMS drug list. Individual payment records are identified as opioid-related payments if at least one listed drug's normalized name is matched to an opioid name. Drug names were normalized by systematically removing special characters and extra spaces, as well as decapitalizing strings. We aggregated the amount of opioid-related payments (excluding buprenorphine and methadone) from August 2013 to 2015 for comparison with the payment estimates in Hadland et al. (2017), the first publication we are aware of to consider direct-payments for opioids. Our estimate of opioid payments is $40.93 million, which is nearly identical to Hadland et al.'s result ($41.01 million).

B. Mandatory Prescription Drug Monitoring Programs

MPDMP is defined as a PDMP where query is mandatory by law for prescribers under certain circumstances (Buchmueller and Carey, 2018). The status of the "must access" provision of PDMPs by June 2016 was collected from the Prescription Drug Abuse Policy System (PDAPs) (PDAPS, 2018). PDAPs reported whether checking with a PDMP was mandatory for prescribers for at least some patients. The effective dates of more recent MPDMPs by January 2018 were collected from the National Alliance for Model State Drug Laws (NAMSDL) and various state legislature databases. The number of states implementing MPDMPs increased from 11 as of January 2014 to 26 as of January 2018. The implementation status and date of MPDMPs are illustrated in Figure 1. Alaska adopted its MPDMP since July 2017, which is not demonstrated in this Figure.

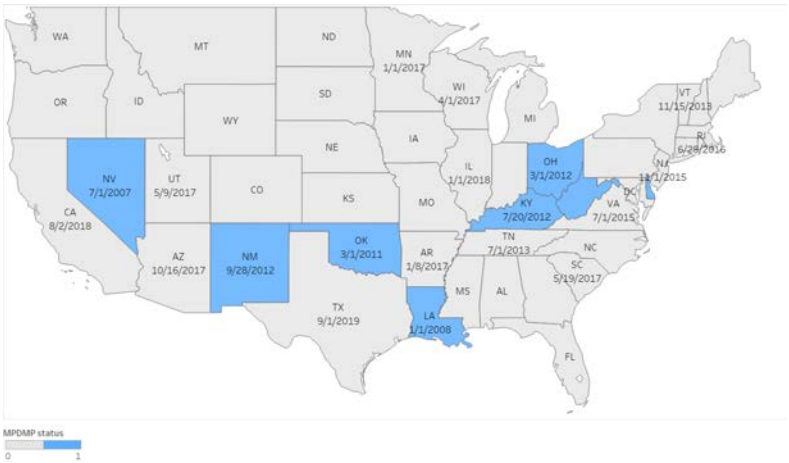
The independent variable of our analysis is the "must access" status of PDMPs, which equals 1 if the state implemented an MPDMP in a full year and equals 0 otherwise. For instance, "must access" in Connecticut (which enacted its MPDMP on 10/1/2015) equals 0 in 2014-2015 and 1 in 2016-2017. There are four states where there are discrepancies in coding MPDMPs between PDAPs and prior studies (Buchmueller and Carey, 2018), including Delaware, Georgia, Louisiana, and Pennsylvania. In a robustness check, we dropped these four states from the analysis. We also consider two alternative codings of MPDMPs in partial years: (i) using the share of months a state implemented its MPDMPs and (ii) excluding certain physicians in states with implemented MPDMPs in partial implementation years.

C. Covariates

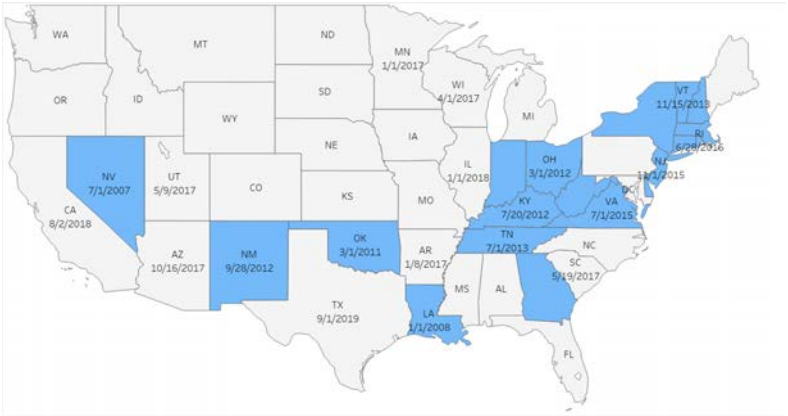
In order to capture exogenous prescribing patterns, we use a physician's annual volume of opioid prescriptions in 2013 (in thousands of daily doses), reported prior to our study period. The data to which we have access is limited to Medicare, and come from the 2013 CMS Prescriber Public Use Files (PUF), a public dataset with information on prescription

Figure 1: State-Level MPDMPs Implemented from 2014 to 2017

(a) By 1/1/2014



(b) By 12/31/2017



Source: MPDMP data were collected from PDAP, NAMSDL, and individual state legislature database.

Notes: This map shows MPDMPs effectively by the end of 2013 and 2017. Alaska and Hawaii were not shown in the maps, given Alaska adopted their MPDMPs since July 2017. The status of MPDMPs was collected from PDAP, NAMSDL, and individual state legislature database.

drug events incurred by Medicare beneficiaries with a Part D prescription drug plan (including Medicare Advantage Prescription Drug plans). Physicians in the 2014-2015 Open Payments data who were not matched to the 2013 Prescriber data were assumed to prescribe no opioid in 2013. The Prescriber PUF data contain 100% of Medicare Part D final-action records submitted within a year for beneficiaries of Medicare Part D, which accounts for a large share of all U.S. retail prescription spending: 42% in 2015, for instance (CMS, 2018a). The 2013 Prescriber PUF Detailed Data provides information about the pre-MPDMP policy-change volume of opioid prescriptions supplied by 807,973

physicians. Although this does not include prescriptions covered by other payer systems or actual prescribing (it only contains information about filled prescriptions) this dataset is the only system with publicly available prescribing information at the physician and drug levels. Because of patient confidentiality requirements, the Part D Prescriber-Drug data do not include the actual number of drugs prescribed by a provider with fewer than 11 Part D drug claims in a year; however, we do know if such physicians prescribed between 1 and 10 claims as opposed to none. Comparing the number of claims in the CMS National Summary Table and the number of claims in the Prescriber-Drug file, we estimated that 13.22% of Medicare Part D claims might be excluded in the 2013 Prescriber PUF Detailed Data for this reason.

Other supplemental data on providers come from the annual Part D Prescriber Summary data (Provider Summary Table) for 2014-2017 and the National Plan and Provider Enumeration System (NPPES); we use them to collect several variables of physician characteristics such as specialty, gender, and years of practice based on NPIs that we used in our empirical analysis. The annual Part D Prescriber Summary data provide names, current business locations, specialty information, and the National Provider Identifiers (NPI) of approximately 1.1 million prescribers.[8] In order to link the Open Payments data to the NPPES and Part D Prescriber Summary datasets, we first obtained NPIs via fuzzy matching using physician names and ZIP codes following previous literature and CMS recommendations in regard to merging Prescriber PUF data with other public datasets (Perlis and Perlis, 2016; CMS, 2018a; Carey et al., 2017). For each year, we used physicians' first names, last names, and current ZIP codes from the Open Payments profile system (without NPIs) and the Part D Prescriber Summary (with NPI), after dropping duplicated physicians to identify NPIs. Nineteen percent of opioid-related payments were excluded from our study as a result of this fuzzy matching exercise. Exclusions from the analysis were made for the physicians in the Open Payments data that lacked any

[8]The Part D PUF data contain information predominantly from individual providers, however they also include a small proportion of organization providers, such as nursing homes, group practices, and non-physician practitioners (CMS, 2018a).

reported drug claims and profile information in the Prescriber PUF data, owing to the assumption that they had not received any reimbursement for Medicare provided services; the PUF contains a census. The final data set of this study includes pharmaceutical payments and control variable data for 694,634 U.S. physicians.

We controlled for a number of practice community characteristics associated with opioid-related pharmaceutical promotion, including county population density, county unemployment rate, median household income, and race and age composition. These county-level demographic and socioeconomic characteristics were extracted from the Robert Wood Johnson Foundation (RWJF) County Health Rankings file (CHR, 2018). In addition, we obtained the percent of adults aged 19 to 64 with insurance at the county by year level from the U.S. Census Bureau's Small Area Health Insurance Estimates program (SAHIE). The physician-level data were mapped to county data using the ZIP-county crosswalk file in the R package noncensus (Boland et al., 2017; Ramey, 2016).

V. Empirical Strategy

To test the effect of MPDMPs on promotional activity, we estimate DD models in this physician-level cross-sectional study. In the basic model, we regress physician-level and annual promotional activity outcomes on the status of the "must access" provision of PDMPs ($Post_{st} \times PDMP_s$) and control for 1) physician characteristics P_{icst} including gender and estimated years of experience; 2) county-level demographic factors (C_{cst}); 3) specialty fixed effects (θ_{sp}) ; 4) county fixed effects (θ_c); and 5) year fixed effects (θ_t). Our base regression model is:

$$Y_{icst} = \beta_0 + \beta_1 Post_{st} \times PDMP_s + \beta_2 HighVolume_{icst} + \beta_p P_{icst} + \beta_c C_{cst} + \theta_{sp} + \theta_c + \theta_t + \epsilon_{icst} \quad (17)$$

Where Y_{icst} is an opioid detailing outcome of physician i in year t, who specialized in

specialty sp with her or his main practice located in county c, state s. The first outcome is whether a physician receives any opioid-related payment from opioid manufactures. The second outcome is the logged amount of payments a physician received within the reported year, conditional on the receipt of opioid-related payments. The third outcome is the logged number of payments (or visits) a physician had received from drug detailers within the reported year in the analysis conditional on the receipt of any pharmaceutical promotion.. $Post_{st} \times PDMP_s$ is 1 if the state has an MPDMP that requires physicians to access the PDMP before prescribing opioids. Gender is 1 if the provider is male. Estimated years of experience are proxied by the number of years since a physician's registration in the NPPES under their current and active NPIs. Since the NPI activities and NPPES registration began in 2005, the maximum estimated years of experience is 12 in our dataset. Each regression contains fixed effects for county and year, and their standard errors are clustered at the state level.

Our theoretical model also provides insights on the expected heterogeneity of MPDMP effects on promotion aimed at physicians according to whether they are high-opioid volume prescribers ($HighVolume$). We use the following triple differences model to examine the hypothesis that high-volume prescribers will see less of a reduction in promotion relative to low-volume prescribers:

$$\begin{aligned} Y_{icst} &= \beta_0 + \beta_1 Post_{st} \times PDMP_s + \beta_2 Post_{st} \times PDMP_s \times HighVolume_{icst} \\ &\quad + \beta_3 HighVolume_{icst} + \beta_p P_{icst} + \beta_c C_{cst} + \theta_{sp} + \theta_t + \theta_c + \epsilon_{icst} \end{aligned} \tag{18}$$

An underlying assumption of the DD method is that absent the intervention, treatment and control groups would have trended similarly. While this is untestable, we draw comfort in situations where prior to the policy change, treatment and control groups experience similar trends in the outcome variable. With the caveat that we have a relatively short-T panel (2014-2017), we apply an event study approach for half-yearly data of opioid detailing. The major concern in our estimation method is the possibility of

policy endogeneity or nonparallel trends: that states implementing an MPDMP were not trending similarly in the dependent variable prior to its implementation to those that do not.

Indeed, Buchmueller and Carey (2018) found some evidence of anticipatory effects of "must-access" PDMPs for the pharmacy shopping outcome. Thus, we may worry that this carries over to detailing outcomes, and that during the months between legislative enactment and implementation, the policy process might involve consultation with medical providers and might encourage them to create PDMP accounts and begin accessing the database (anticipatory effects, which make the observed policy effects look smaller than appropriate). Therefore, opioid makers might strategically change their detailing in response to the upcoming must-access PDMPs. If so, the implementation timing in our event study analysis is fuzzy, with the true post-period beginning earlier than what we code. The event study regression model is:

$$Y_{icsh} = \beta_0 + \sum_{k=[-6,6]} \beta_k PDMP_{sk} + \beta_p P_{icsh} + \beta_c C_{cst} + \theta_{sp} + \theta_h + \theta_c + \epsilon_{icsh} \quad (19)$$

Where Y is an opioid detailing outcome at the physician level over a half-year and $PDMP_{sk}$ equals 1 if state s implemented an MPDMP k half-years ago. For instance, $PDMP_{s-2} = 1$ if state s implemented this policy 2 half-years (or 1 year) ago. We combine all post-periods after the sixth half-year into the sixth ($k = 6$) and all pre-periods more than three years prior into $k = -6$. The most important coefficients are β_ks which show the differences between treatment and control states in the periods prior to and following the policy implementation. Our baseline specification drops the 1-half-year lag of MPDMPs. The alternative specification drops the implemented half-year of MPDMPs.

VI. Results

A. Summary Statistics

In our study period, opioid manufacturers made $65.7 million payments directly to physicians: $15 million in 2014, $20.5 million in 2015, $14.9 million in 2016, and $15.3 million in 2017. The most common type of opioid-related promotion was spending on food and beverage (99.3% of all visits and 21.9% of all monetary payments); however, speaking fees represented the largest share of promotion in dollars (56.8% of all opioid-related payments but only 2.2% of all visits in 2014-2017). Oxycodone (including Oxycontin) was the most frequently promoted among the opioids investigated in our study (i.e., fentanyl, hydrocodone, morphine, oxycodone and other opiates), accounting for 29.7% of opioid-related promotional activities. However, opioid makers spent the largest proportion of promotion dollars on fentanyl (33.8%).

The number of promotional observations in our baseline cross-sectional analysis is 1.81 million, extracted from over 40 million Open Payments records and relevant data of 694,634 U.S. physicians. Table 1 provides summary statistics for the dependent variables, physician characteristics, and county characteristics. On average, 7% of these physicians received at least some opioid-related pharmaceutical payment within a year, ranging from less than 1 dollar to $292,740/year. Conditional to the receipt of these payments, the average amount of opioid-related pharmaceutical payments per year was $418. While per year 6.9% of these physicians received at least one opioid-related sponsored meal, only 0.3% of physicians received a non-meal promotion. Interestingly, 8.5% of physicians in this study were the top 5% prescribers of opioids to Medicare patients in 2013 and only 35.2% of these top prescribers received opioid-related payments.

Table 1: Summary Statistics

	Mean	Standard Deviation	P75	P95	Min	Max
Pharmaceutical Payments						
Receipt of opioid detailing (%)	7.0	(25.5)	0	100	0	100
Amount of opioid payments ($)	29.2	(1206.4)	0	18.3	0	292,740.7
Number of opioid payments	0.4	(4.0)	0	1	0	385
Receipt of opioid meals (%)	6.9	(25.4)	0	100	0	100
Amount of opioid meals ($)	6.7	(61.8)	0	17.9	0	7,927.9
Number of opioid meals	0.4	(3.6)	0	1	0	278
Receipt of opioid non-meal payments (%)	0.3	(5.5)	0	0	0	100
Amount of opioid non-meal payments ($)	20.7	(1055.9)	0	0	0	255,631.3
Number of opioid non-meal payments	0.02	(0.8)	0	0	0	178
Receipt of dermatology-related detailing (%)	2.6	(16.0)	0	0	0	100
Amount of dermatology-related payments ($)	7.5	(450.2)	0	0	0	216313.8
Number of dermatology-related payments	0.1	(1.3)	0	0	0	227
Receipt of hypertensives-related detailing (%)	0.8	(9.0)	0	0	0	100
Amount of hypertensives-related payments ($)	0.9	(369.8)	0	0	0	487,501.0
Number of hypertensives-related payments	0.02	(0.5)	0	0	0	97
Receipt of antidiabetics-related detailing (%)	12.4	(32.9)	0	100	0	100
Amount of antidiabetics-related payments ($)	53.0	(1,420.5)	0	108.9	0	268,153.4
Number of antidiabetics-related payments	1.3	(6.1)	0	7	0	395
Receipt of thyroid-agents-related detailing (%)	3.4	(18.1)	0	0	0	100
Amount of thyroid-agents-related payments ($)	9.0	(395.0)	0	0	0	123,970.9
Number of thyroid-agents-related payments	0.09	(0.8)	0	0	0	155
Physician Characteristics						
Male provider (%)	72.2	(44.8)	100	100	0	100
Experience years since NPI registration	8.6	(2.3)	10	11	0	12
Top 5% prescribers (%)	8.5	(27.9)	0	100	0	100
Top 2% prescribers (%)	0.03	(0.2)	0	0	0	1
Internal medicine (%)	27.3	(44.5)	100	100	0	100
Family medicine and practice (%)	12.4	(33.0)	0	100	0	100
Surgery (%)	9.5	(29.3)	0	100	0	100
Hematology and Oncology (%)	2.0	(13.8)	0	0	0	100
Radiation oncology (%)	0.6	(7.4)	0	0	0	100
Neurology (%)	2.0	(14.0)	0	0	0	100
Pain medicine (%)	0.4	(6.1)	0	0	0	100
Physical medicine and rehabilitation (%)	1.0	(9.7)	0	0	0	100
Anesthesiology (%)	0.4	(6.6)	0	0	0	100
Other (%)	44.5	(49.7)	100	100	0	100
County Characteristics						
1,000 residents per mile^2	3.1	(9.6)	2.2	11.6	0.00004	72.9
Unemployment rate (%)	5.1	(1.5)	6	8	1	24
Median household income	60,003.5	(16,118.6)	67197	92,310	22,045	136,191
Aged 18-64 population (%)	62.6	(3.2)	64.2	68.4	35.9	82.9
Aged >65 populations (%)	14.9	(3.6)	16.4	21.6	4.1	56.9
White Americans(%)	59.8	(20.6)	76.4	91.1	2.8	98.1
Non-Hispanic African Americans (%)	14.4	(13.2)	20.6	42.5	0	85.3
Hispanic Americans (%)	17.2	(15.8)	25.2	48.6	0.4	96.3
Asian and other race (%)	8.6	(7.4)	9.4	22.1	0.3	87.2
Observations (physician × year)	1,810,918					

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: The dataset represents one observation per physician per year. We take Open Payments data 2014-2017 and merge with information on a physician's characteristics from NPPES 2017, and with information on a physician's 2013 opioid prescribing volume from the 2013 Prescriber PUF data. Opioid-related payments were identified based on each payment record's up-to-five listed drug names and a comprehensive list of opioid drugs from CMS and CDC.

B. Regression Results: the Effect of MPDMPs on Opioid-Related Pharmaceutical Promotion

Table 2 presents the estimated results of our DD estimated effects of MPDMPs on three measures of opioid detailing. Column 1 reports the results of estimating Equation 17 on the likelihood of receiving opioid-related payments. For a typical physician, an MPDMP is associated with a substantial decline in the likelihood of receiving any opioid-related payments: 0.9 percentage points or 12.8% of the average likelihood (model 1, $p<0.01$). Columns 3 and 5 report the estimations on two measures of the intensive margin of detailing in the models (logged amount of payments and logged number of visits, respectively), which are conditional on getting any detailing visits. MPDMPs appear to have considerable overall effects on these measures among physician-recipients; an MPDMP reduces the dollar amount of opioid-related pharmaceutical promotion by 8.1% ($p<0.01$), and it reduces the frequency of these promotions by 7.3% ($p<0.01$). These results provide evidence supporting our first hypothesis regarding whether MPDMPs impede opioid detailing. Moreover, a physician's previous high-volume status in prescribing opioids for Medicare part D patients is a strong predictor of opioid-related pharmaceutical payments in subsequent years.

The triple differences models are presented in columns 2, 4, and 6 in order to examine the hypothesis that high-volume prescribers will see less of a reduction in promotion relative to low-volume prescribers. The data support this hypothesis for one intensive margin of pharmaceutical detailing of opioid products: frequency of direct-to-physician payments. In particular, results in column 6 imply that MPDMPs only reduce the frequency of these promotions by 2.9% among the top 5% prescribers, compared to a 7.3% reduction for a typical physician.

The results also show that physicians who are male or more experienced are more likely to receive opioid promotion. Even after controlling for county fixed effects, we found that population density is positively associated with the prevalence of opioid detailing

Table 2: Effects of PDMP on Opioid-Related Physician Payments

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Post×PDMP	-0.0092**	-0.010**	-0.074**	-0.089***	-0.066**	-0.090***
	(0.0033)	(0.0035)	(0.027)	(0.022)	(0.023)	(0.023)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0073)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.017		0.039		0.064*
		(0.011)		(0.030)		(0.026)
Male provider	0.0071***	0.0071***	0.13***	0.13***	0.10***	0.10***
	(0.00082)	(0.00082)	(0.014)	(0.014)	(0.013)	(0.013)
Experience (years)	0.0020***	0.0020***	-0.018***	-0.018***	-0.0072+	-0.0073+
	(0.00013)	(0.00013)	(0.0042)	(0.0042)	(0.0038)	(0.0039)
1,000 residents per square mile	0.019***	0.019***	-0.27***	-0.27***	-0.16*	-0.15*
	(0.0045)	(0.0045)	(0.072)	(0.072)	(0.073)	(0.072)
Unemployment rate (%)	0.00013	0.0029	0.61	0.62	1.68+	1.70+
	(0.11)	(0.12)	(1.21)	(1.21)	(0.86)	(0.86)
Median household income, logged	-0.023	-0.023	-0.12	-0.12	-0.11	-0.11
	(0.014)	(0.014)	(0.17)	(0.17)	(0.16)	(0.16)
Aged 18-64 population (%)	-0.0012	-0.0011	0.0025	0.0032	0.015	0.016
	(0.0033)	(0.0033)	(0.031)	(0.031)	(0.034)	(0.034)
Aged >65 populations (%)	-0.0027	-0.0026	-0.029	-0.029	-0.032	-0.031
	(0.0038)	(0.0038)	(0.040)	(0.040)	(0.034)	(0.034)
Non-Hispanic African American (%)	-0.0055*	-0.0055*	0.022	0.022	0.032	0.032
	(0.0026)	(0.0026)	(0.027)	(0.028)	(0.027)	(0.028)
Hispanic American (%)	0.0056*	0.0056*	-0.079**	-0.079**	-0.075**	-0.074**
	(0.0023)	(0.0023)	(0.027)	(0.027)	(0.023)	(0.022)
Asian and other race %	0.0050	0.0051	-0.092*	-0.091*	-0.10**	-0.10**
	(0.0031)	(0.0031)	(0.035)	(0.035)	(0.032)	(0.032)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Dep. Variable SD	0.25	0.25	1.30	1.30	1.10	1.10
Observation	1,810,918	1,810,918	126,422	126,422	126,422	126,422
R^2	0.19	0.19	0.25	0.25	0.29	0.29

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: The dataset represents one observation per physician per year. Models 1 & 2: the dependent variable is an binary indicator that a physician received payments in a year. Models 3-6 are regressions conditional to the receipt of opioid-related payments; the dependent variables are the dollar amount of promotion or the number of discrete payments and take log-transformed values. County fixed effects and year fixed effects were included in each regression. Clustered Standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

among Medicare Part D prescribers; it is negatively correlated with intensive margins of such detailing, however. Additionally, physicians in counties with greater proportions of non-Hispanic African Americans are more likely to receive opioid-related payments from opioid manufacturers. These results may reflect the marketing strategies of drug companies which target high-volume prescribers for drug detailing (more experienced doctors and those with previous high-volume status in prescribing opioids) and prescribers

in more profitable markets (higher concentrations of White Americans and more populous communities).

C. Regression Results: Nonparallel Trend Assumption

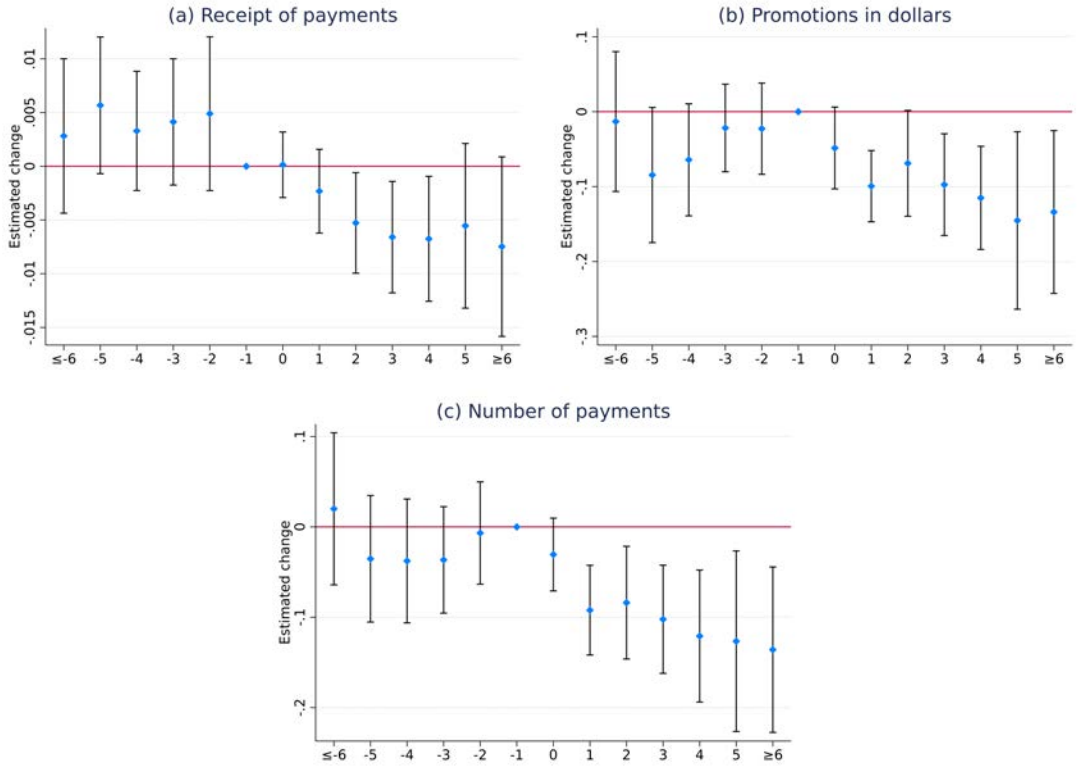
We investigate the underlying assumption of our DD approach for causal inference by testing the possibility of policy endogeneity or nonparallel trends, where states implementing an MPDMP were not similar prior to implementation to those that did not.

Figure 2 and Table A1 provide the results of the event study analyses. By estimating equation (19), the event study analyses represent a standard test for the nonparallel trend assumption. A significant coefficient of any pre-trend periods (β_{-6} to β_{-2}) may suggest a violation of our underlying assumption because it indicates significant differences between mandatory and non-mandatory states on these outcomes prior to the implementation of this policy. At the 5 percent level, the estimates of β_{-6} to β_{-2} are not significantly different from zero (1 half-year prior to the implementation of MPDMPs). Our event study results are not sensitive to the alternative specification, which drops the implemented half-year of MPDMPs (models 4-6) rather than the 1-half-year lag of MPDMPs (models 1-3). Thus, the event study analyses do not suggest concern regarding nonparallel trends or policy endogeneity for our DD models. Furthermore, the coefficients on MPDMP leads indicate that the effects of MPDMPs on opioid detailing gradually increase over time.

D. Regression results: Heterogeneity by Rurality

Prior work suggests that Oxycontin and other strong opioids were more aggressively promoted in rural communities surrounding the Appalachian region (Wininger, 2004; Keyes et al., 2014; Monnat, 2019). In addition, prescription opioid abuse is common across the U.S., but it is historically most prevalent in rural areas and small urban regions (J et al., 2007; Palombi et al., 2018). We thus compare the effect of MPDMPs on opioid detailing in rural versus urban regions, using the percentage of the county population living in rural areas as of the 2010 Census to obtain two subsamples equivalent in sample

Figure 2: Event Study Analysis



Notes: The dataset represents one observation per physician per half-year. $t[-6;6]$ represents t half-years prior to or after the implementation of the PDMP "must access". The figures plot the estimated difference and its 95% confidence intervals for each period prior or after the implementation of must access PDMPs. We excluded observations in one half-year prior to the implementation of MPDMPs from the analysis. The analyses in (b) and (c) are conditional to the receipt of opioid-related payments.

size: rural and urban. Counties with less than 1.06% (the third quartile of % rural population) of the population living in rural areas were classified as urban, while counties with more than 16.68% (the first quartile) were classified as rural. We did not utilize the classification approach of the U.S. Census Bureau, which uses 50% of the population living in rural areas as a threshold to define a rural county, but we note that this approach would have led to a much smaller subsample of rural counties.

Our data show that only 4.7% of rural physicians (in the rural subsample) were top 5% prescribers, while 14.7% of urban physicians were among the top prescribers. Therefore, as expected, only 5.1% of rural physicians received payments from opioid makers compared to 9% of urban physicians. Interestingly, rural physician-recipients tended to receive more promotion measured as the annual dollar amount of payment or the number

of visits. On average, conditional to the receipt of opioid payments, a physician in the rural subsample received $654.1 in a year from opioid manufacturers, compared to only $191.6 by a typical urban physician. The average number of visits for rural physician-recipients was 6.8; the average number for urban physician-recipients was 5.3.

Table 3 reports the results of estimating Equations (17) and (18) for the effect of MPDMPs on three measures of opioid detailing for physicians practicing in rural and urban regions. We see a relatively stronger negative effect of MPDMPs on the likelihood of receiving opioid detailing in rural areas compared to the estimated effect in the full sample (a 1.5 percentage point decline, which is equivalent to 30% of average likelihood, compared to a 1.4 percentage point decrease, which equals only 15.5% of average likelihood). Interestingly, among top 5% prescribers in rural areas the effect of PDMP is positive (a 2.1 percentage point increase in the likelihood of receiving payments, $p<0.05$). These results are consistent with the heterogeneous margins of pharmaceutical promotion in these geographical areas. That is, rural markets tend to have smaller margins per dollar of promotion due to their greater traveling costs and smaller density of providers compared to urban markets. Therefore, we expect stronger negative feedback effects of MPDMPs on opioid detailing received by rural low-volume prescribers compared with urban low-volume prescribers, given the same restriction by MPDMPs among both populations.

E. Regression results: Markets with Differential Margins of Promotion

Table 4 shows the estimated effects of MPDMPs on various pre-existing markets with different potential margins of promotion. In order to classify the bottom 25% counties and top 25% counties in terms of pre-existing volumes of prescription opioids written by the physicians in our dataset (Panels 1 and 2), we aggregated the days' supply of opiates prescribed by all physicians in 2013 to the county level. The most noticeable difference

Table 3: Effects of PDMP: Rural vs. Urban Physicians

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Panel 1: practice in rural counties						
Post×PDMP	-0.015*	-0.017**	0.046	0.034	-0.019	-0.038
	(0.0058)	(0.0058)	(0.060)	(0.048)	(0.051)	(0.046)
Top 5% prescribers	0.24***	0.24***	0.63***	0.62***	0.68***	0.67***
	(0.012)	(0.011)	(0.038)	(0.040)	(0.032)	(0.025)
Post×PDMP×Top 5% prescribers		0.038*		0.038		0.065
		(0.015)		(0.083)		(0.072)
Dep. Variable Mean	0.05	0.05	3.97	3.97	1.02	1.02
Dep. Variable SD	0.22	0.22	1.44	1.44	1.13	1.13
Observation	452,751	452,751	23,085	23,085	23,085	23,085
R^2	0.16	0.16	0.20	0.20	0.25	0.25
Panel 2: practice in urban counties						
Post×PDMP	-0.014*	-0.014*	-0.091	-0.10+	-0.093	-0.12+
	(0.0054)	(0.0061)	(0.056)	(0.056)	(0.064)	(0.064)
Top 5% prescribers	0.23***	0.23***	0.42***	0.41***	0.46***	0.45***
	(0.0085)	(0.012)	(0.019)	(0.024)	(0.018)	(0.022)
Post×PDMP ×Top 5% prescribers		0.0056		0.019		0.043
		(0.015)		(0.030)		(0.030)
Dep. Variable Mean	0.09	0.09	3.65	3.65	0.99	0.99
Dep. Variable SD	0.29	0.29	1.13	1.13	1.01	1.01
Observation	452,686	452,686	40,706	40,706	40,706	40,706
R^2	0.20	0.20	0.28	0.28	0.30	0.30

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files. The percentage of the county population living in rural areas comes from the 2010 Census.

Notes: Using the rural population ratio, we defined rural counties with more than the third quartile of rural population and urban areas with less than the first quartile of the population living in rural areas. The dataset represents one observation per physician per year. Models 1 & 2: the dependent variable is an binary indicator that a physician received payments in a year. Models 3-6 are regressions conditional to the receipt of opioid-related payments; the dependent variables are the dollar amount of promotion or the number of discrete payments and take log-transformed values. County fixed effects and year fixed effects were included in each regression. Clustered standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

comes from the estimated effects of MPDMPs on the likelihood of receiving opioid detailing, by physicians from the top vs. the bottom pre-existing markets of prescription opioids. While MPDMPs significantly reduced the likelihood that physicians received promotion in counties with the lowest pre-existing volume of prescription opioids by 1.1 percentage points (p<0.001), these programs did not significantly change this extensive margin of opioid detailing in counties with the highest volume of opioid prescriptions. Furthermore, high-volume prescribers of opioids were more likely to receive opioid detail-

ing following MPDMPs. The differences in the intensive margins of detailing are trivial among these markets.

Table 4: Effects of PDMP: Small vs. Large Opiate Markets

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Panel 1: bottom 25% counties in pre-existing opioid prescriptions in Medicare						
Post×PDMP	-0.011***	-0.012***	-0.092**	-0.095**	-0.072**	-0.088**
	(0.0029)	(0.0032)	(0.031)	(0.031)	(0.027)	(0.028)
Top 5% prescribers	0.24***	0.24***	0.49***	0.49***	0.53***	0.51***
	(0.0073)	(0.010)	(0.021)	(0.025)	(0.019)	(0.023)
Post×PDMP×Top 5% prescribers		0.00070		0.0091		0.041
		(0.012)		(0.030)		(0.027)
Dep. Variable Mean	0.08	0.08	3.73	3.73	1.00	1.00
Observation	898,417	898,417	68,403	68,403	68,403	68,403
R^2	0.19	0.19	0.27	0.27	0.29	0.29
Panel 2: top 25% counties in pre-existing opioid prescriptions in Medicare						
Post×PDMP	0.0016	-0.00095	-0.067+	-0.094*	-0.057+	-0.090*
	(0.0039)	(0.0040)	(0.036)	(0.037)	(0.031)	(0.033)
Top 5% prescribers	0.25***	0.24***	0.58***	0.56***	0.65***	0.63***
	(0.012)	(0.013)	(0.031)	(0.030)	(0.027)	(0.022)
Post×PDMP×Top 5% prescribers		0.043*		0.073		0.090+
		(0.017)		(0.057)		(0.048)
Dep. Variable Mean	0.06	0.06	3.90	3.90	1.06	1.06
Observation	912,501	912,501	58,019	58,019	58,019	58,019
R^2	0.19	0.19	0.23	0.23	0.29	0.29
Panel 3: bottom 25% counties in pre-existing insurance rates						
Post×PDMP	-0.026***	-0.028***	0.070	0.11+	0.015	0.033
	(0.0056)	(0.0060)	(0.066)	(0.063)	(0.050)	(0.049)
Top 5% prescribers	0.21***	0.21***	0.49***	0.51***	0.57***	0.58***
	(0.0099)	(0.011)	(0.039)	(0.038)	(0.030)	(0.031)
Post×PDMP×Top 5% prescribers		0.017		-0.087		-0.038
		(0.018)		(0.10)		(0.082)
Dep. Variable Mean	0.07	0.07	3.87	3.87	1.02	1.02
Observation	372,252	372,252	24,717	24,717	24,717	24,717
R^2	0.18	0.18	0.23	0.23	0.28	0.28
Panel 4: top 25% counties in pre-existing insurance rates						
Post×PDMP	-0.0026	-0.0025	-0.080+	-0.10*	-0.065	-0.092*
	(0.0028)	(0.0032)	(0.046)	(0.047)	(0.044)	(0.044)
Top 5% prescribers	0.27***	0.27***	0.59***	0.57***	0.62***	0.59***
	(0.013)	(0.017)	(0.032)	(0.032)	(0.030)	(0.026)
Post×PDMP×Top 5% prescribers		-0.0020		0.065		0.084*
		(0.021)		(0.048)		(0.039)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Observation	573,426	573,426	38,359	38,359	38,359	38,359
R^2	0.19	0.19	0.25	0.25	0.28	0.28

Notes: We used the aggregate days' supply of opioids in 2013 of matched Medicare prescribers to define the bottom 25% opiate markets vs. top 25%. We used the percent of adults aged 19 to 64 with insurance for countries in 2013 to identify the bottom 25% vs. top 25% in pre-existing insurance rates. The dataset represents one observation per physician per year. County fixed effects and year fixed effects were included in each regression. Clustered standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Panels 3-4 of table 4 report the estimates for counties with the lower adult insurance rates and for counties with the highest adult insurance rates. We utilized the county-level insurance rates in 2013 (percent of adults aged 18-64, with insurance) from the SAHIE to classify these markets. Counties with lower insurance rates are expected to have lower demand and medical use for prescription opioids; therefore, these counties plausibly have lower margins of detailing and subsequently become less attractive markets for pharmaceutical sales representatives given the same restrictions on providers. As expected, MPDMPs significantly reduced the likelihood of physicians' receiving opioid detailing in counties with the lowest insurance rates by 2.6 percentage points ($p<0.01$), but did not change this outcome for physicians in counties with the highest insurance rates. We found opposing results in the intensive margins of detailing: MPDMPs significantly reduced amounts and frequency of payments among low-volume prescribers in counties with top insurance rates (columns 4 and 6, Panel 4), but did not change this outcome for physicians in counties with bottom insurance rates (columns 4 and 6, Panel 3). These findings are consistent with the heterogeneous margins of pharmaceutical promotion due to difference in insurance coverage by county.

F. Regression Results: Effect of MPDMPs by Type of Opioid Detailing and Specialty

The comprehensive Open Payments data allow us to examine the effect of MPDMPs on specific types of detailing. This analysis compares the estimated effects of MPDMPs on two main types of opioid related payments: meals and non-meal promotion (including speaking fees, consulting fees, education expenses, and traveling costs, which are directly beneficial to physicians and require reporting to the CMS Open Payments database), reported in Table 5. We found that MPDMPs reduce the likelihood of receiving meals offered by 0.9 percentage points ($p<0.01$), which equals the overall effect of MPDMPs on any opioid detailing (Panel 1). Nevertheless, there is no significant difference between

implementing and control states when it comes to non-meal promotions to physicians (Panel 2). This finding is expected, because most non-meal promotions are offered to experts or specialists whose detailing might provide a larger return than their peers.

Table 5: Effects of PDMP on Different Types of Opioid Detailing

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Panel 1: industry-sponsored meals						
Post×PDMP	-0.0091**	-0.010**	-0.067*	-0.083**	-0.059*	-0.084***
	(0.0032)	(0.0034)	(0.028)	(0.024)	(0.024)	(0.024)
Top 5% prescribers	0.24***	0.24***	0.51***	0.50***	0.58***	0.57***
	(0.0073)	(0.0097)	(0.013)	(0.012)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.017		0.043		0.064*
		(0.012)		(0.027)		(0.025)
Dep. Variable Mean	0.07	0.07	3.75	3.75	1.02	1.02
Dep. Variable SD	0.25	0.25	1.14	1.14	1.08	1.08
Observation	1,810,918	1,810,918	125,533	125,533	125,533	125,533
R^2	0.19	0.19	0.28	0.28	0.29	0.29
Panel 2: Non-Meal Payments: Speaker, Consultant, Education, Travel						
Post×PDMP	-0.00080	-0.00083	-0.23	-0.064	-0.080	-0.073
	(0.00075)	(0.00076)	(0.34)	(0.39)	(0.19)	(0.16)
Top 5% prescribers	0.017***	0.017***	-0.17	-0.093	0.24***	0.25***
	(0.0013)	(0.0014)	(0.13)	(0.14)	(0.032)	(0.048)
Post×PDMP×Top 5% prescribers		0.00048		-0.27		-0.011
		(0.0033)		(0.25)		(0.12)
Dep. Variable Mean	0.003	0.003	5.13	5.13	1.10	1.10
Dep. Variable SD	0.06	0.06	3.34	3.34	1.12	1.12
Observation	1,810,918	1,810,918	5,575	5,575	5,575	5,575
R^2	0.05	0.05	0.33	0.33	0.27	0.27

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: The dataset represents one observation per physician per year. Non-meal payments include direct-to-physician payments in speaker promotional programs, pharmaceutical consulting fees, education programs, and travelling. Models 1 & 2: the dependent variable is an binary indicator that a physician received payments (meals or non-meal payments) in a year. Models 3-6 are regressions conditional to receipt of payments; the dependent variables are the dollar amount of promotion or the number of discrete payments and take log-transformed values. County fixed effects and year fixed effects were included in each regression. Clustered standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table A2 presents the estimated effects of MPDMPs for different types of physicians. It is not surprising that physicians in Pain Medicine were most frequently visited by opioid sales representatives (72% of these physicians had received some opioid-related

promotion between 2014 and 2017). We found that MPDMPs reduce the likelihood of receiving opioid detailing by Pain Medicine physicians by 7.4 percentage-points (Panel 1, $p<0.001$), which is equivalent to 10.3% of the average likelihood and relatively modest compared to the decline in the overall average likelihood of the full dataset (12.8% of the average likelihood). In addition, these programs did not significantly reduce the extensive margins of payments. We found a similar pattern among Rehabilitation and Physical Medical doctors. Interestingly, the results imply that sales representatives substantially dropped their visits and amounts of pharmaceutical gifts to primary care physicians (including family medicine and internal medicine doctors), especially among low-volume prescribers of opioids (Panels 4 and 5).

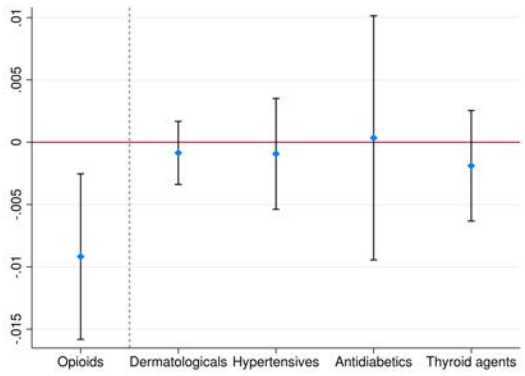
G. Placebo Tests and Sensitivity Checks

We examine the effect of MPDMPs on the detailing of non-opioid classes of drugs as a placebo test. We linked the Multum Lexicon Addendum Files to State Drug Utilization Data (SDUD) to identify high-priced drugs for the most prescribed therapeutic drug groups that are not relevant to opiate products. These top therapeutic classes by prescriptions include dermatologicals, anti-hypertensives, anti-diabetes drugs, and thyroid agents (Aitken et al., 2016). We used the 2012 and 2013 SDUD files to calculate average Medicaid spending per prescription for each NDC, then ranked the drugs by spending per prescription within each selected therapeutic class. We kept the top 5 percentile of each drug class and extracted drug names for our placebo test. In particular, Amlodipine, Azor, Bidil, Caduet, Diovan, Exforge, Lotrel, and Tribenzor are included hypertensives. Thyroid agents include Cytomel, Levothroid, Levoxyl, Liothyroni, Propylthio, Synthroid, Tapazole, and Tirosint. Anti-diabetics consist of Actoplus, Actos, Bydureon, Byetta, Fortamet, Glumetza, Humalog, Humulin, Metformin, Novolog, Prandin, and Symlinpen. Aczone, Azelex, Benzaclin, Betamethas, Calcipotri, Carac, Clindagel, Clobetasol, and Clobex are some high-priced dermatologicals. The point and interval estimates at the 5 percent level of the effect of MPDMPs were plotted in Figure 3. We find no effects of

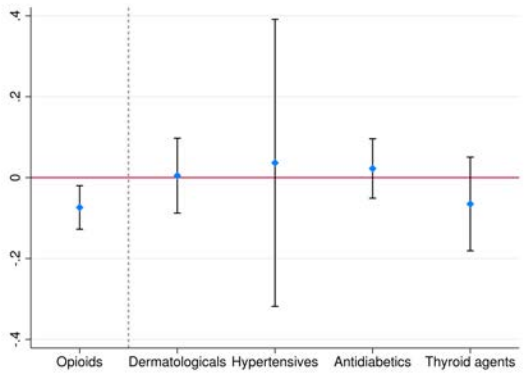
MPDMPs on three measures of non-opioid pharmaceuticals. These results are expected since MPDMPs do not create burdensome prescribing requirements for these drugs.

Figure 3: Placebo tests - Effects of PDMP on non-opioid Detailing payments

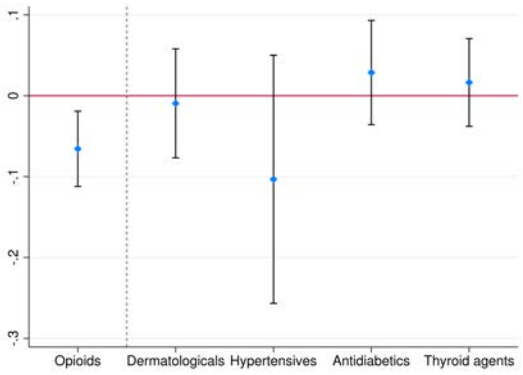
(a) Receipt of payments



(b) promotion in dollars



(c) Number of promotion



Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: The dataset represents one observation per physician per year. The figures plot the estimated coefficient of Post×PDMP and its 95% confidence intervals in 5 regressions for each outcome of relevant pharmaceutical payments: (i) opioid products, (ii) dermatology drugs, (iii) anti-hypertensive drugs, and (v) anti-diabetes drugs, and thyroid agents. The comparison drug groups include high-priced drugs of the most prescribed groups of drugs which are not relevant opiate products.

We test the sensitivity in our analysis's coding of MPDMPs through three alternative classifications in Table A3: (1) fractionalized treatment in partial years, (2) dropping observations of partial MPDMP implementation years, and (3) dropping four implementing states with coding discrepancies. Panel 1 reports our baseline regression results, where MPDMP equals 1 if the state implemented an MPDMP in a full year and equals 0 oth-

erwise. Panel 2 reports the alternative coding of the MPDMP status: that is, in partial years of implementation, MPDMP is equal to the share of months a state implemented PDMP. This specification is appropriate if MPDMPs have immediate effects on detailing. The point estimates of this specification are close to those of the baseline regressions, but the standard errors on Post×PDMP are larger. Consequently, the estimated effects of MPDMPs are less significant using this coding approach. These results are consistent with our aforementioned event studies that MPDMPs may not have immediate effects on opioid detailing. In panel 3, we excluded the observations of treatment states in partial years. The estimated effects of MPDMPs are larger in magnitude and more significant than the estimates in the baseline regressions. In panel 4, we excluded physicians from DE, LA, NV, OH, OK, and VT in the analysis due to the PDAP coding of these states' particular MPDMPs , as noted in prior work (Buchmueller and Carey, 2018). The results are close to the baseline results. Interestingly, these results provide evidence confirming both hypotheses in our theoretical framework: MPDMPs impede opioid detailing but high-volume prescribers have seen less of a reduction in promotion relative to low-volume prescribers.

During the study period, a number of states implemented regulations directly targeting pain clinics. Pain clinics are facilities where the majority of patients are provided treatment for pain. Unlike MPDMPs, which might affect the mass of providers including primary care physicians, pain clinic laws only affect the behavior of a small portion of physicians by requiring state oversight and other requirements concerning the ownership and operation of these clinics. We collected the timing of pain clinics laws from PDAPS and adjusted for this co-occurring policy of MPDMPs when estimating the effects of MPDMPs on opioid detailing (Panel 2, Table A4). Practicing in states with pain clinic laws, physicians are more likely to receive opioid detailing (columns 1 and 2). Accounting for pain clinic laws slightly reduces the estimated effects of MPDMPs on the likelihood of receiving opioid detailing: a 0.9 percentage point decrease compared with a 0.87 percentage point decrease in the baseline specification. Prescribers in several states face other

restrictions on prescription opioids, particularly regulatory limits on initial prescription. We obtained the timing of day-limit regulations from Davis et al. (2019). Controlling for this policy does not modify our estimated effects of MPDMPs (Panel 3, A4).

VII. Conclusion

With the advent of online and electronic versions of MPDMPs, state prescribing restrictions have achieved greater reporting frequency and greater coverage of all prescribing activities (Buchmueller and Carey, 2018). This has resulted in MPDMPs encompassing more current and complete depictions of patient prescription history. Informing medical providers of potential misuse and thus reducing diversion of opioids has been the underlying principle motivating policy implementation. However, economic theory points out another mechanism at play: regulation restricting the access of drugs such as the access mandate of MPDMPs might reduce the rate of return on detailing and correspondingly reduce the detailing activities of opioid manufacturers. We found a substantially negative effect of MPDMPs on the measure of opioid detailing incidence. An MPDMP leads to a 0.9 percentage point decline in the likelihood of receiving an opioid payment which is equivalent to a 12.8% decline in average likelihood. Among physician-recipients of opioid detailing, an MPDMP considerably reduces the dollar amount of opioid-related pharmaceutical promotion by 8.1% and the frequency of these promotions by 7.3%. The event study analysis suggests there is no violation of a parallel trends assumption and placebo checks on detailing of high-priced drugs of the most prescribed non-opioid drug classes (dermatologicals, anti-hypertensives, anti-diabetes, and thyroid agents) perform satisfactorily, thus we argue this study provides the first evidence of the causal, negative effect of MPDMPs on opioid-related detailing.

Pharmaceutical companies are believed to have tracked prescriptions by purchasing prescription records and then strategically targeting high-volume prescribers for drug detailing (Fugh-Berman and Ahari, 2007). An example of this scheme is a fentanyl bribery

case against Insys Therapeutics Inc. Using pharmacy data, the defendants conspired to bribe high-volume prescribers of their highly potent fentanyl products via speaker programs. The targeted prescribers were practitioners who either prescribed unusually high volumes of rapid-acting opioids, or practitioners that had demonstrated a capacity to do so (Department of Justice, 2019). Therefore, it is economically important to understand the effect of MPDMPs on the prescribing behavior of these physicians. We provide moderate evidence on the diminishing negative effect of MPDMPs on the frequency of opioid detailing among high-volume prescribers, particularly the top 5% of prescribers in 2013, the year prior to our study period. MPDMPs reduce the frequency of opioid detailing only by 3% among high-volume prescribers, compared to the overall 7.3% decline in this intensive margin of detailing. We found a stronger negative effect of MPDMPs on the extensive margin of detailing in rural areas compared to urban areas, smaller pre-existing volumes of prescription opioids vs. larger volumes, and low adult insurance coverage vs. high adult insurance coverage.

The findings of this study provide important contributions to the economics literature on pharmaceutical promotion, and have substantial policy implications. The results inform policy makers of the empirical evidence on the effectiveness of MPDMPs - a strong version of PDMPs aimed toward impeding opioid marketing activities aimed at physicians. Therefore, implementing MPDMPs might reduce the highly concerning influence of drug detailing on the prescribing behavior as physicians will tend to receive less payments from the pharmaceutical industry. The event study analyses also suggest a slightly increasing effect of MPDMPs over time. Given the 2018 announcement by Purdue Pharma (the largest marketer to physicians among opioid makers as of 2015) that they ceased all opioid promotional activities aimed at physicians, this increases salience of studies that examine causal effects of regulation regarding pharmaceutical marketing.

Although we have undertaken several complementary analyses to assess robustness of our results, our study has several limitations. First, we used Medicare Part D data only to characterize whether a physician is a high prescriber at baseline. It is possible

that this approach may exclude some high-volume prescribers to other types of patients, potentially introducing noise in the analysis.

Second, we rely upon the pharmaceutical manufacturers' self-reporting of which drugs were linked (marketed) to each payment, and there is a limit of five drug mentions per record, thus measurement error is possible. For instance, some specific payments from a multi-drug maker could be tied to one or more opioids in addition to multiple non-opioid drugs. By reaching the maximum number of linked drugs to a record, opioids could be omitted in that record, leading to data errors.

Third, the measure of opioid detailing is the observed equilibrium quantity of opioid detailing received by physicians rather than direct measures of opioid manufacturers' actual investments and efforts. However, it is less plausible that the estimated decline in the equilibrium quantity of detailing following MPDMPs can be attributable to physicians' response to MPDMPs by accepting fewer meetings with opioid sales representatives. The mandates of PDMPs do not have any provisions regulating the financial ties between opioid manufacturers and prescribers. Furthermore, PDMPs are not new to prescribers. PDPMs date back to the late 1930s, with a new wave of implementation which began in the early 2000s that typically allows prescribers access to an electronic PDMP system (Bao et al., 2016).

Fourth, the CMS Open Payments database provides a census of drug detailing activities aimed at physicians but not other medical providers such as nursing homes, nurses, nurse practitioners, and physician assistants. Our analysis also does not cover other aspects of drug marketing, including counter-detailing, national and local advertising of drugs, and patient-oriented marketing. Nevertheless, the focus of this study is the impact of MPDMPs on opioid detailing received by current medical practitioners who are directly regulated by this mandate and major targets of the marketing force from opioid manufacturers. For example, nurse practitioners and physicians assistants may prescribe opioids under certain regulations, but there is no mandate in the Sunshine Act for any promotion towards them to be reported, except for payments passed through a physician

(Centers for Medicare & Medicaid Services (CMS) et al., 2013). Future research could utilize consumer-directed drug advertising data and records of promotion aimed at teaching hospitals in the Open Payments data to examine any shift in drug marketing efforts by opioid manufacturers attributable to MPDMPs and declined ROI of opioid detailing.

Appendix

Table A1: Event Study Analysis - Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline specification			**Alternative specification**		
	Receiving payments	Amount of payments	Number of visits	Receiving payments	Amount of payments	Number of visits
≥ 6 half-years prior	0.0028	-0.013	0.020	0.0027	0.035	0.051
	(0.0036)	(0.046)	(0.042)	(0.0044)	(0.057)	(0.044)
5 half-years prior	0.0057+	-0.085+	-0.035	0.0055	-0.036	-0.0047
	(0.0032)	(0.045)	(0.035)	(0.0039)	(0.056)	(0.036)
4 half-years prior	0.0033	-0.064+	-0.038	0.0032	-0.016	-0.0071
	(0.0028)	(0.037)	(0.034)	(0.0033)	(0.048)	(0.035)
3 half-years prior	0.0041	-0.022	-0.037	0.0040	0.027	-0.0059
	(0.0029)	(0.029)	(0.029)	(0.0032)	(0.038)	(0.030)
2 half-years prior	0.0049	-0.023	-0.0068	0.0048	0.026	0.024
	(0.0036)	(0.030)	(0.028)	(0.0037)	(0.038)	(0.027)
1 half-year prior	reference	reference	reference	-0.00014	0.048+	0.031
				(0.0015)	(0.027)	(0.020)
Implemented half-year	0.00014	-0.048+	-0.031	reference	reference	reference
	(0.0015)	(0.027)	(0.020)			
1 half-year after	-0.0023	-0.099***	-0.092***	-0.0025	-0.051*	-0.062**
	(0.0019)	(0.024)	(0.025)	(0.0019)	(0.024)	(0.020)
2 half-years after	-0.0053*	-0.069+	-0.084**	-0.0054*	-0.021	-0.053+
	(0.0023)	(0.035)	(0.031)	(0.0024)	(0.047)	(0.031)
3 half-years after	-0.0066*	-0.097**	-0.10**	-0.0067**	-0.049	-0.072**
	(0.0026)	(0.034)	(0.030)	(0.0024)	(0.039)	(0.023)
4 half-years after	-0.0068*	-0.12**	-0.12**	-0.0069**	-0.067	-0.090*
	(0.0029)	(0.034)	(0.036)	(0.0026)	(0.044)	(0.037)
5 half-years after	-0.0055	-0.15*	-0.13*	-0.0057	-0.097	-0.096+
	(0.0038)	(0.059)	(0.050)	(0.0034)	(0.065)	(0.052)
≥ 6 half-years after	-0.0075+	-0.13*	-0.14**	-0.0076*	-0.085	-0.11*
	(0.0042)	(0.054)	(0.046)	(0.0037)	(0.058)	(0.045)
Dep. Variable Mean	0.06	3.62	0.87	0.06	3.62	0.87
Dep. Variable SD	0.24	1.23	0.97	0.24	1.23	0.97
Obs.	2,991,644	177,299	177,299	2,991,644	177,299	177,299

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: The dataset represents one observation per physician per half-year. In models 1-3, we excluded observations in one half-year prior to the implementation of MPDMPs from the analysis. In models 4-6, we excluded observations in implemented years of MPDMPs from the analysis. The analyses in models 2-4 & 5-6 are conditional to the receipt of opioid-related payments. County fixed effects and year fixed effects were included in each regression. Clustered Standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table A2: Effects of PDMP by Speciality

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Panel 1: Pain Medicine						
Post×PDMP	-0.074***	-0.073*	0.0071	0.045	0.063	0.086
	(0.017)	(0.029)	(0.23)	(0.30)	(0.19)	(0.25)
Top 5% prescribers	0.24***	0.24***	0.77***	0.78***	0.73***	0.74***
	(0.024)	(0.027)	(0.098)	(0.10)	(0.060)	(0.058)
Post×PDMP×Top 5% prescribers		-0.0019		-0.062		-0.038
		(0.038)		(0.20)		(0.15)
Dep. Variable Mean	0.72	0.72	5.33	5.33	2.37	2.37
Panel 2: Anesthesiology						
Post×PDMP	-0.045	-0.057	-0.19	-0.26	-0.097	-0.15
	(0.033)	(0.036)	(0.18)	(0.18)	(0.11)	(0.12)
Top 5% prescribers	0.31***	0.30***	0.83***	0.79***	0.83***	0.80***
	(0.018)	(0.017)	(0.073)	(0.087)	(0.069)	(0.071)
Post×PDMP×Top 5% prescribers		0.027		0.11		0.092
		(0.034)		(0.12)		(0.15)
Dep. Variable Mean	0.65	0.65	5.17	5.17	2.22	2.22
Panel 3: Rehabilitation and Physical Medicine						
Post×PDMP	-0.054***	-0.062***	-0.14	-0.18	-0.11	-0.13
	(0.015)	(0.017)	(0.091)	(0.12)	(0.070)	(0.095)
Top 5% prescribers	0.40***	0.40***	0.90***	0.87***	0.88***	0.87***
	(0.014)	(0.015)	(0.056)	(0.072)	(0.050)	(0.055)
Post×PDMP×Top 5% prescribers		0.023		0.073		0.044
		(0.028)		(0.11)		(0.10)
Dep. Variable Mean	0.49	0.49	4.81	4.81	1.89	1.89
Panel 4: Internal Medicine						
Post×PDMP	-0.0085*	-0.011**	-0.082***	-0.12***	-0.075**	-0.13***
	(0.0035)	(0.0039)	(0.021)	(0.028)	(0.025)	(0.028)
Top 5% prescribers	0.23***	0.22***	0.23***	0.20***	0.37***	0.33***
	(0.010)	(0.012)	(0.028)	(0.029)	(0.022)	(0.020)
Post×PDMP×Top 5% prescribers		0.020		0.095+		0.13***
		(0.016)		(0.050)		(0.033)
Dep. Variable Mean	0.07	0.07	3.58	3.58	0.82	0.82
Panel 5: Family Practice						
Post×PDMP	-0.018+	-0.024*	-0.11*	-0.092*	-0.11**	-0.11**
	(0.010)	(0.010)	(0.041)	(0.045)	(0.034)	(0.034)
Top 5% prescribers	0.18***	0.18***	0.29***	0.30***	0.31***	0.31***
	(0.0081)	(0.010)	(0.017)	(0.018)	(0.015)	(0.016)
Post×PDMP×Top 5% prescribers		0.027*		-0.034		-0.0073
		(0.012)		(0.032)		(0.028)
Dep. Variable Mean	0.16	0.16	3.53	3.53	0.88	0.88
Panel 6: Hematology and Oncology						
Post×PDMP	-0.023	-0.021	-0.0025	-0.0045	0.071	0.077
	(0.022)	(0.021)	(0.15)	(0.15)	(0.098)	(0.10)
Top 5% prescribers	0.081***	0.099***	0.42**	0.41*	0.30***	0.33***
	(0.018)	(0.024)	(0.15)	(0.17)	(0.081)	(0.086)
Post×PDMP×5% prescribers		-0.063+		0.048		-0.15
		(0.034)		(0.41)		(0.17)
Dep. Variable Mean	0.15	0.15	3.46	3.46	0.63	0.63

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: Internal Medicine category also includes Immunology, Cardiology, Critical Care, Endocrinology, Gastroenterology, Geriatric, Infectious Medicine, Nephrology, Pulmonary, Rheumatology, Sports Medicine, and Hepatology. Models 1 & 2: the dependent variable is an binary indicator that a physician received payments (meals or non-meal payments) in a year. Models 3-6 are regressions conditional to receipt of payments. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table A3: Sensitivity Analyses - Different PDMP Codings

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Panel 1: baseline model						
Post×PDMP	-0.0092**	-0.010**	-0.074**	-0.089***	-0.066**	-0.090***
	(0.0033)	(0.0035)	(0.027)	(0.022)	(0.023)	(0.023)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0073)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.017		0.039		0.064*
		(0.011)		(0.030)		(0.026)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Observation	1,810,918	1,810,918	126,422	126,422	126,422	126,422
R^2	0.19	0.19	0.25	0.25	0.29	0.29
Panel 2: fractionized treatment in partial years						
Post×PDMP	-0.0072	-0.0078+	-0.053	-0.059	-0.044+	-0.056+
	(0.0044)	(0.0046)	(0.041)	(0.043)	(0.026)	(0.030)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0073)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.016		0.027		0.051+
		(0.011)		(0.031)		(0.026)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Observation	1,810,918	1,810,918	126,422	126,422	126,422	126,422
R^2	0.19	0.19	0.25	0.25	0.29	0.29
Panel 3: exclude observations of partial implementation years of MPDMPs						
Post×PDMP	-0.021**	-0.022***	-0.12***	-0.14***	-0.089***	-0.11***
	(0.0060)	(0.0061)	(0.032)	(0.031)	(0.024)	(0.024)
Top 5% prescribers	0.24***	0.24***	0.54***	0.52***	0.59***	0.57***
	(0.0073)	(0.0099)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.019		0.043		0.070*
		(0.012)		(0.031)		(0.026)
Dep. Variable Mean	0.07	0.07	3.80	3.80	1.03	1.03
Observation	1,690,661	1,690,661	117,640	117,640	117,640	117,640
R^2	0.19	0.19	0.25	0.25	0.29	0.29
Panel 4: exclude states where ambiguity in codings of MPDMPs exists						
Post×PDMP	-0.0093**	-0.011**	-0.069*	-0.10***	-0.063*	-0.10***
	(0.0033)	(0.0035)	(0.027)	(0.021)	(0.024)	(0.023)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0081)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.022+		0.083**		0.096***
		(0.012)		(0.025)		(0.024)
Dep. Variable Mean	0.07	0.07	3.80	3.80	1.02	1.02
Observation	1,664,989	1,664,989	115,331	115,331	115,331	115,331
R^2	0.19	0.19	0.25	0.25	0.29	0.29

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files.

Notes: The dataset represents one observation per physician per year. Panel 1 reports our baseline regression results where MPDMP equals 1 if the state implemented an MPDMP in a full year and equals 0 otherwise. Panel 2 reports the alternative coding of the MPDMP status, that is in partial years of implementation, MPDMP equals to the share of months a state implemented PDMP. In panel 3, we excluded the observations of treatment states in these partial years. Panel 4: we excluded physicians from DE, LA, NV, OH, OK, VT in the analysis due to the discrepancy in coding these MPDMPs by PDAPs and prior studies. Clustered Standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table A4: Sensitivity Analyses - Controlling for Co-Occurring Policies

	(1)	(2)	(3)	(4)	(5)	(6)
	Receiving payments		**Amount of payments**		**Number of visits**	
Panel 1: baseline model						
Post×PDMP	-0.0092**	-0.010**	-0.074**	-0.089***	-0.066**	-0.090***
	(0.0033)	(0.0035)	(0.027)	(0.022)	(0.023)	(0.023)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0073)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP×Top 5% prescribers		0.017		0.039		0.064*
		(0.011)		(0.030)		(0.026)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Observation	1,810,918	1,810,918	126,422	126,422	126,422	126,422
R^2	0.19	0.19	0.25	0.25	0.29	0.29
Panel 2: Controlling for Pain Clinic Management Laws						
Post×PDMP	-0.0087*	-0.0099**	-0.076**	-0.091***	-0.067**	-0.091***
	(0.0034)	(0.0035)	(0.027)	(0.023)	(0.023)	(0.023)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0073)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP× Top 5% prescribers		0.017		0.039		0.064*
		(0.011)		(0.030)		(0.026)
Pain clinic laws	0.013***	0.013***	-0.061*	-0.061*	-0.038	-0.037
	(0.0020)	(0.0020)	(0.025)	(0.025)	(0.030)	(0.030)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Observation	1,810,918	1,810,918	126,422	126,422	126,422	126,422
R^2	0.19	0.19	0.25	0.25	0.29	0.29
Panel 3: Controlling for Days Limits						
Post×PDMP	-0.0093**	-0.010**	-0.072*	-0.088***	-0.063**	-0.088***
	(0.0032)	(0.0034)	(0.027)	(0.023)	(0.022)	(0.021)
Top 5% prescribers	0.25***	0.24***	0.54***	0.53***	0.59***	0.57***
	(0.0073)	(0.0096)	(0.015)	(0.015)	(0.015)	(0.015)
Post×PDMP× Top 5% prescribers		0.017		0.040		0.065*
		(0.011)		(0.030)		(0.026)
Days-limit laws	0.0029	0.0029	-0.034	-0.035	-0.055**	-0.059**
	(0.0019)	(0.0019)	(0.033)	(0.033)	(0.018)	(0.018)
Dep. Variable Mean	0.07	0.07	3.81	3.81	1.03	1.03
Observation	1,810,918	1,810,918	126,422	126,422	126,422	126,422
R^2	0.19	0.19	0.25	0.25	0.29	0.29

Source: Pharmaceutical payment data come from the CMS's 2014-2017 Open Payments repository. Physician characteristics data come from the CMS's 2013 Part D PUF data, 2017 NPPES. Community characteristics were extracted from the RWJF files. Pain clinic laws come from PDAPs. We obtained data of laws limiting the initial prescribing from Davis et al. (2019).

Notes: The dataset represents one observation per physician per year. Models 1 & 2: the dependent variable is an binary indicator that a physician received payments (meals or non-meal payments) in a year. Models 3-6 are regressions conditional to receipt of payments; the dependent variables are the dollar amount of promotion or the number of discrete payments and take log-transformed values. County fixed effects and year fixed effects were included in each regression. Clustered Standard errors at the state level in parentheses. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

References

Ahmad, F., L. Rossen, M. Spencer, M. Warner, and P. Sutton (2019). Provisional drug overdose death counts. Report NCHS data brief, no 273., National Center for Health Statistics. Accessed: 2019-08-09.

Aitken, M., M. Kleinrock, K. Pennente, J. Lyle, D. Nass, and L. Caskey (2016). Medicines use and spending in the us a review of 2015 and outlook to 2020 [internet]. *IMS Institute for Healthcare Informatics*.

Alpert, A., D. Powell, and R. L. Pacula (2018). Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids. *American Economic Journal: Economic Policy 10*(4), 1–35.

Bao, Y., Y. Pan, A. Taylor, S. Radakrishnan, F. Luo, H. A. Pincus, and B. R. Schackman (2016). Prescription drug monitoring programs are associated with sustained reductions in opioid prescribing by physicians. *Health Affairs 35*(6), 1045–1051.

Berndt, E. R., L. T. Bui, D. H. Lucking-Reiley, and G. L. Urban (1996). The roles of marketing, product quality, and price competition in the growth and composition of the us antiulcer drug industry. In *The economics of new goods*, pp. 277–328. University of Chicago Press.

Boland, M. R., P. Parhi, P. Gentine, and N. P. Tatonetti (2017). Climate classification is an important factor in assessing quality-of-care across hospitals. *Scientific Reports 7*(1), 4948.

Buchmueller, T. C. and C. Carey (2018). The effect of prescription drug monitoring programs on opioid utilization in medicare. *American Economic Journal: Economic Policy 10*(1), 77–112.

Carey, C. M., E. M. Lieber, and S. Miller (2017). Drug firms' payments and physicians' prescribing behavior in medicare part d.

CDC (2018). The ambulatory care drug database system. https://www2.cdc.gov/drugs/applicationnav1.asp. Accessed: 2018-01-30.

Centers for Medicare & Medicaid Services (CMS), H. et al. (2013). Medicare, medicaid, children's health insurance programs; transparency reports and reporting of physician ownership or investment interests. final rule. *Federal register 78*(27), 9457.

Chai, G., J. Xu, J. Osterhout, M. A. Liberatore, K. L. Miller, C. Wolff, M. Cruz, P. Lurie, and G. Dal Pan (2018). New opioid analgesic approvals and outpatient utilization of opioid analgesics in the united states, 1997 through 2015. *Anesthesiology: The Journal of the American Society of Anesthesiologists 128*(5), 953–966.

CHR (2018). County health rankings and roadmaps. http://www.countyhealthrankings.org. Accessed: 2018-01-30.

CMS (2018a). Medicare part d opioid prescribing mapping tool methodology. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Downloads/Opioid_Methodology.pdf. Accessed: 2018-01-30.

CMS (2018b). Medicare provider utilization and payment data: Part d prescriber. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Part-D-Prescriber.html. Accessed: 2018-01-30.

Dave, D., M. Deza, and B. P. Horn (2018). Prescription drug monitoring programs, opioid abuse, and crime. Technical report, National Bureau of Economic Research.

Davis, C. S., A. J. Lieberman, H. Hernandez-Delgado, and C. Suba (2019). Laws limiting the prescribing or dispensing of opioids for acute pain in the united states: A national systematic legal review. *Drug and alcohol dependence 194*, 166–172.

DeJong, C., T. Aguilar, C.-W. Tseng, G. A. Lin, W. J. Boscardin, and R. A. Dudley (2016). Pharmaceutical industry–sponsored meals and physician prescribing patterns for medicare beneficiaries. *JAMA internal medicine 176*(8), 1114–1122.

Department of Justice (2019). Founder and Four Executives of Insys Therapeutics Convicted of Racketeering Conspiracy. [Online; accessed 12-August-2019].

Evans, W. N., E. M. Lieber, and P. Power (2019). How the reformulation of oxycontin ignited the heroin epidemic. *Review of Economics and Statistics 101*(1), 1–15.

Fugh-Berman, A. and S. Ahari (2007). Following the script: how drug reps make friends and influence doctors. *PLoS Medicine 4*(4), e150.

Gonul, F. F., F. Carter, E. Petrova, and K. Srinivasan (2001). Promotion of prescription drugs and its impact on physicians' choice behavior. *Journal of Marketing 65*(3), 79–90.

Greene, J. A. (2004). Attention to 'details': etiquette and the pharmaceutical salesman in postwar american. *Social Studies of Science 34*(2), 271–292.

Hadland, S. E., M. S. Krieger, and B. D. Marshall (2017). Industry payments to physicians for opioid products, 2013–2015. *American journal of public health 107*(9), 1493–1495.

J, C. T., S. Hilary, I. J. A., and M. Alvaro (2007). Relationship between therapeutic use and abuse of opioid analgesics in rural, suburban, and urban locations in the united states. *Pharmacoepidemiology and Drug Safety 16*(8), 827–840.

Keyes, K. M., M. Cerdá, J. E. Brady, J. R. Havens, and S. Galea (2014). Understanding the rural–urban differences in nonmedical prescription opioid use and abuse in the united states. *American journal of public health 104*(2), e52–e59.

Lakdawalla, D., N. Sood, and Q. Gu (2013). Pharmaceutical advertising and medicare part d. *Journal of health economics 32*(6), 1356–1367.

Mallatt, J. (2018). The effect of prescription drug monitoring programs on opioid prescriptions and heroin crime rates. *Available at SSRN 3050692*.

Meinhofer, A. (2018). Prescription drug monitoring programs: The role of asymmetric information on drug availability and abuse. *American Journal of Health Economics 4*(4), 504–526.

Monnat, S. M. (2019). The contributions of socioeconomic and opioid supply factors to us drug mortality rates: Urban-rural and within-rural differences. *Journal of Rural Studies 68*, 319–335.

Pacula, R. L., D. Powell, et al. (2018). A supply-side perspective on the opioid crisis. *Journal of Policy Analysis and Management 37*(2), 438–446.

Palombi, L. C., C. A. St Hill, M. S. Lipsky, M. T. Swanoski, and M. N. Lutfiyya (2018). A scoping review of opioid misuse in the rural united states. *Annals of epidemiology 28*(9), 641–652.

Paulozzi, L. J., E. M. Kilbourne, and H. A. Desai (2011). Prescription drug monitoring programs and death rates from drug overdose. *Pain medicine 12*(5), 747–754.

PDAPS (2018). Prescription drug abuse policy system. http://pdaps.org. Accessed: 2018-01-30.

Perlis, R. H. and C. S. Perlis (2016). Physician payments from industry are associated with greater medicare part d prescribing costs. *PloS one 11*(5), e0155474.

Radakrishnan, S. (2013). The impact of information in health care markets: Prescription drug monitoring programs and abuse of opioid pain relievers. Report, Working Paper, Cornell University.

Ramey, J. A. (2016). U.S. Census Regional and Demographic Data.

Robinson, J. (1933). The theory of imperfect competition. *Quarterly Journal of Economics*.

Sacks, D. W., A. Hollingsworth, T. D. Nguyen, and K. I. Simon (2019). Can policy affect initiation of addictive substance use? evidence from opioid prescribing. Technical report, National Bureau of Economic Research.

Stigler, G. J. (1961). The economics of information. *Journal of political economy 69*(3), 213–225.

Van Zee, A. (2009). The promotion and marketing of oxycontin: commercial triumph, public health tragedy. *American Journal of Public Health 99*(2), 221–227.

Wen, H., B. R. Schackman, B. Aden, and Y. Bao (2017). States with prescription drug monitoring mandates saw a reduction in opioids prescribed to medicaid enrollees. *Health Affairs 36*(4), 733–741.

Wininger, P. J. (2004). Pharmaceutical overpromotion liability: the legal battle over rural prescription drug abuse. *Ky. LJ 93*, 269.