Curbing Pharma Influence: The Effect of Marketing Restrictions on Physicians' Prescribing Behavior

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Abstract

The impact of direct-to-physician marketing and its regulations on physicians' prescribing behavior is a subject of ongoing debate. While the pharmaceutical industry advocates for the necessity of keeping doctors informed about new drugs through these channels, critics voice concerns about potential distortions in prescribing patterns. To address the possible adverse effects of these interactions, New Jersey implemented a policy in January 2018 imposing significant restrictions on direct-to-physician marketing, including limits on small meal payments and caps on substantial payments for consulting and speaking. Using the New Jersey policy as an exogenous source of variation and two federal administrative databases in a difference-in-difference event-study design, I estimate a reduction of about 27% in marketing activities directed at New Jersey doctors compared to their peers in New York and Pennsylvania. Reduced form analyses reveal that prescribers in New Jersey decrease the prescription volume of marketed drugs by approximately 6% across extensive and intensive margins. Moreover, the overall proportion of branded prescriptions decreases by about 0.66 percentage points. The predominant source of the observed behavioral changes originates from prescribers with high level of exposure to pharmaceutical promotions, with no significant change among those with limited or without such engagement. The policy equally affected both new and old drug prescriptions, suggesting that doctor-pharma financial ties may not be purely informational.

Keywords: Health policy, Prescription drugs, Marketing, Physician behavior

JEL Classification: D04, H75, I11, I18

1 Introduction

In 2019, the Centers for Medicare and Medicaid Services (CMS) reported that the medical industry, including drug and medical device manufacturers, disbursed 10.55 million payments totaling 3.7 billion dollars to physicians and medical professionals nationwide (CMS, 2019).[1] Direct-to-Physician Marketing (DTPM) consists of about 85% of drug firms' advertising budget, and 93% of physicians reported some type of relationship with the pharmaceutical industry (Trusts, 2015; Campbell et al., 2007). Due to substantial investments made by pharmaceutical companies in these marketing initiatives, a vast population of doctors engaged, and the potential adverse effects of industry payments on prescribing behavior and patient welfare, the DTPM activities and their regulations necessitate thorough scrutiny.[2]

While proponents of the practice argue that these marketing interactions aim to educate doctors about new drugs, opponents express doubts about this claim, emphasizing such monetary transactions may be utilized to incentivize doctors to prescribe particular drugs. According to a pharmaceutical industry trade group, these encounters are crucial for ensuring that healthcare professionals possess the latest, most accurate information about prescription medicines, which play an increasingly pivotal role in patient healthcare (PhRMA, 2020). Conversely, opponents contend that pharmaceutical firms are not suitable entities to educate doctors about new drugs. As expressed in an interview by Marcia Angell, a prominent critic [3]: "They [drug companies] have managed to make a lot of people believe that they are also somehow educating about drugs. That can't be. It's as though you look to beer companies to educate you about alcoholism. There is a conflict of interest there" (Frontline, 2002).

Over the past two decades, state and federal authorities have voiced concerns about the possible adverse effects of industry-physicians financial relationships on prescribing

[1] These numbers are only for the general payments. In addition, firms paid 6 billion for research payments and 1.42 billion for ownership and investment interest.

[2] Marcia Angell, , underscores the magnitude of pharmaceutical companies' focus on influencing physicians, stating, "Yes, the companies spend a lot of money on consumer ads... But, the lion's share of their attempts to manipulate the situation goes to the doctors, because they are the ones who write the prescriptions" (Frontline, 2002).

[3] Marcia Angell is a faculty member at Harvard Medical School. She was the first woman to serve as editor-in-chief of the New England Journal of Medicine and she is the author of the book "The Truth About the Drug Companies: How They Decieve us and What To Do About It".

behavior and patient outcomes. In a rare and important fraud alert in November 2020, the Department of Health and Human Services Office of the Inspector General (OIG) reported the resolution of numerous fraud cases violating various federal statutes linked to industry-sponsored speaker programs.[4,5] This event underscores an urgent economic and ethical need to closely scrutinize such relationships.

Over a decade ago, to increase transparency regarding these interactions, the Physician Payments Sunshine Act (PPSA) mandated all drug and medical device firms to track and report their payments to physicians for public release.[6] Preceding the enactment of PPSA, several states had initiated their own disclosure and restriction policies to curb interactions between manufacturers and healthcare professionals.[7] However, evaluating the effectiveness of these policies has been challenging due to the absence of detailed transfer data, the lack of suitable counterfactuals, and limited information regarding the nature of the payments involved. The current literature remains inconclusive on whether regulating payments is beneficial. In particular, it is necessary to identify marketing channels that pose a more significant threat and are primarily utilized to sway physicians' prescribing patterns. Furthermore, the intricate dynamics of relationships between firms and healthcare practitioners add another layer of complexity, making it difficult to reach a consensus about the true effects of these encounters on prescription behavior and patient welfare.[8]

In this study, I provide new insights into the impact of restrictive policies on DTPM and prescribing behavior by linking the comprehensive Open Payments dataset—which records monetary and in-kind payments made by drug firms to physicians from 2014 to 2019 [9]—with doctors' prescriptions for Medicare Part D enrollees. The focus is on

[4] https://oig.hhs.gov/documents/special-fraudalerts/865/SpecialFraudAlertSpeakerPrograms.pdf

[5] According to Adashi and Cohen (2021) only 6 such alerts have been issued by the OIG over the last two decades.

[6] PPSA is solely a disclosure policy and does not ban or restrict industry-physicians financial relationships.

[7] Before PPSA, states such as MA, VT, WV, DC, CA, and NV had implemented various levels of disclosure and restriction mandates on DTP marketing. Further details are elaborated in Section 2.2.

[8] Spurling et al. (2010) provides a comprehensive review of medical literature concerning the impact of marketing activities on the quality, quantity, and cost of prescribed drugs. Overall, the authors assert that the primary hindrance to obtaining a clear answer to the question lies in the limitations inherent in the existing body of research.

[9] I choose 2019 as the last year of the analysis due to significant effects of the pandemic on payments from firms to doctors.

utilizing a unique New Jersey (NJ) policy implemented in 2018, which restricted various interaction channels between doctors and pharmaceutical firms and evaluate its effects on DTPM and physicians' prescribing behavior.[10]

Before the policy, physicians in New Jersey (NJ) and neighboring states of New York (NY) and Pennsylvania (PA) exhibited very similar trends in the frequency and dollar value of payments received from firms and prescription volume across intensive and extensive margins.[11] Following the policy enactment in January 2018, substantial changes occurred in the trajectories of payments and prescriptions. Overall, NJ prescribers received $22.30 less per drug annually, a 27% reduction from the pre-policy mean of $83.70. This decrease was driven by significant reductions in food-related payments (32%), compensation other than consulting (30%), and travel-related remunerations (21%).[12] The overall reduction in payment frequency was modest at 3%, largely due to the prevalence of food payments, which were not restricted by the policy.[13] However, substantial declines were observed in other categories, with a 29% decrease in compensation other than consulting , 26% in travel payments, and 13% in consulting fees. The reduced form results confirm that NJ doctors decreased prescription volumes of marketed drugs in both extensive (6.9% for total claims, 5.6% for the number of patients) and intensive margins (5.9% for total days supply) post-policy. Additionally, drug costs show a relative decline of 5% at the 10% significance level.[14]

Pharmaceutical companies often target high-prescribing doctors who are typically key opinion leaders with significant influence over their peers. In addition, due to their higher prescription volumes, these prescribers can have a greater impact on overall pre-

[10]According to Sullivan (2018), New Jersey is the first state to implement capping physician incomes and applying the regulations not to pharmaceutical companies but to the physicians themselves. Some other states all have varying restrictions on practitioner relationships with industry, but none of them restrict income.

[11]The choice of neighboring states as controls mitigates concerns regarding fundamental differences between treated and control physicians. These states are similar in terms of population and socioeconomic variables. Various robustness checks were conducted to ensure that the results are not driven by the choice of control states; including the implementation of a synthetic control approach, which is robust to the arbitrary choice of control states. Details about robustness to choice of control units are available in the appendix.

[12]Compensation other than the consulting category mainly consists of payments made to speakers during promotional speaking events. Refer to the appendix for a detailed definition of each category.

[13]The NJ policy imposes restrictions on the dollar value of meals, not on their frequency. Please refer to Section 2.1 for more details.

[14]According to Medicare's definition, drug cost is based on the amounts paid by the Part D plan, Medicare beneficiaries, government subsidies, and any other third-party payers. Therefore, it is closer to the list prices announced for all drugs.

scription volumes, expenditures, and patient outcomes. Therefore, it is crucial to examine whether these physicians are disproportionately affected by the policy. I focus on the top 5% of highest-paid physicians in NJ, NY, and PA, who received an average of $42,085 annually before the policy. They experienced a decrease of $643.7 in industry payments per drug annually, representing a 20% reduction from the pre-policy mean of $3,068. Additionally, there was a 10.5% decrease in payment frequency, primarily due to fewer speaker program engagements. The policy's impact on prescription behavior was also greater for this group, resulting in an approximately 10% reduction, which is nearly twice the amount observed among average doctors. These findings indicate that the policy had a more significant effect on high-receiving doctors compared to their average counterparts.

I conduct several additional analyses to shed light on underlying mechanisms. First, a comparison of branded versus generic prescriptions reveals that the proportion of brand prescriptions—typically targeted by drug firms—decreased by about 0.66 percentage points, while the proportion of generic prescriptions increased accordingly. This suggests a shift in prescribing behavior from brand-name drugs to generics, which has significant cost-saving implications. Second, heterogeneity by payment intensity reveals that most changes in prescription behavior originated from doctors with high levels of interactions with firms with no effects on prescribers with minimal engagement. Third, if the pharmaceutical industry's claim that payments are purely informational were accurate, we would expect reductions in prescription volumes to affect only the newest drugs, leaving older drugs unchanged. However, estimates based on the FDA approval dates of drugs reveal that the policy similarly impacted both newer and older drugs. These findings collectively support the causal effect of restrictions on industry promotions and prescribing behavior, providing further evidence that the financial relationship between physicians and pharmaceutical firms may not be solely informational.

Numerous studies in medical literature have found a positive association between the receipt of pharmaceutical promotions and increased prescribing volumes, higher drug costs, and lower prescribing quality (DeJong et al., 2016b; Adair and Holmgren, 2005; Dolovich et al., 1999; Freemantle et al., 2000; Grundy et al., 2013; Annapureddy et al., 2020; Yeh et al., 2016; Fleischman et al., 2016; Orlowski and Wateska, 1992; Brax et al.,

2017; Mitchell et al., 2021; DeJong et al., 2016a; Wood et al., 2017; Perlis and Perlis, 2016; Ornstein et al., 2016). In a systematic review of 101 studies, Mitchell et al. (2021) found that 89 studies identified a positive association between increased prescription of marketed drugs, increased prescribing costs, and higher prescription of branded drugs. However, most of these studies did not consider the selection problem (i.e., drug firms tend to make these payments to heavy prescribers) and therefore cannot provide causal interpretations.

Several studies in economics and marketing examine the effects of timing of marketing payments on prescribing behavior (Carey et al., 2021; Agha and Zeltzer, 2022; Shapiro, 2018). Carey et al. (2021) utilize the Open Payments database and Medicare's claim database from 2013 to 2015 in an event study design to explore the effects of these payments on physicians' prescription behavior and the quality of their prescribed drugs. They find that the number of patients and expenditures on the marketed drugs increase after the payments. The increase is substantial, representing a 7.6% rise in expenditures. Agha and Zeltzer (2022) examine large compensation payments to key opinion leaders in an event study and find substantial direct and spillover effects. They find that payments lead to increased prescriptions for the marketed drug by both the paid physician and their peers. Over three years, marketed anticoagulant prescriptions rose by 23%, with peer spillovers contributing a quarter of the increase. DeJong et al. (2016b) find that doctors who receive modest meal payments, generally below $20, are more likely to prescribe brand drugs where generic alternatives are available.

Some other papers (Larkin et al., 2017; Li et al., 2022; Guo et al., 2020; King and Bearman, 2017; Grennan et al., 2018) look at the effects of disclosure or more restrictive policies at the federal, state, and medical school levels on prescription behavior, most of which were enacted before the passage of the Physician Payments Sunshine Act (PPSA) and thus used limited data, unable to leverage the rich data published due to PPSA. Li et al. (2022) uses the Open Payments database to examine the impact of the first federal law (PPSA) on prescription patterns, comparing Massachusetts and Vermont as control states due to their similar prior disclosure policies. Their event study finds that PPSA significantly reduced branded drug prescriptions with no effect on generics, indicating the law's success in lowering drug spending by cutting branded prescriptions, at least in

the short term. King and Bearman (2017) show that state policies banning or limiting gifts from pharmaceutical representatives to doctors are likely to be more effective than disclosure policies alone. Guo et al. (2020) examines the effects of Massachusetts' industry payment disclosure policy on physicians' prescribing behavior, focusing on border counties in the neighboring states as the comparison group. They find that the 2009 disclosure policy led to a decline in prescriptions across all drug classes, including generics. This unexpected decrease suggests that physicians may become more cautious and self-monitoring due to the disclosure, which could be seen as an unintended negative consequence of the policy. Larkin et al. (2017) analyze the impact of restrictive measures that some medical centers imposed on detailing between 2006 and 2012 in a descriptive study. They find a modest but significant decline in prescribing detailed drugs after policy enactment across the majority of these medical centers in five states. Grennan et al. (2018) use a small sample of drugs and variations in hospital policies banning pharmaceutical representatives, finding that a meal increases the promoted statin prescription by about 70%.

This study contributes fresh insights to the field on multiple fronts. First, to my knowledge, it marks the first comprehensive examination of the impact of statewide regulation on a spectrum of firm-doctor interactions, ranging from modest payments for meals to substantial fees for speaking engagements and consulting, and their influence on prescribing patterns. Second, by analyzing the policy's impact on different channels of pharmaceutical promotion, this study offers fresh insights into identifying which channels are primarily used to influence prescribing behavior. Third, various heterogeneity analyses highlight specific types of prescribers and drugs that are more susceptible to being affected by marketing activities. Fourth, this study sheds light on how restrictive policies can facilitate the transition from branded to generic prescribing with substantial cost-saving implications for patients and payers. Fifth, unlike studies that focus on a single drug or drug class, this paper examines all Part D drugs, making the findings more generalizable.[15] Sixth, the data used in the majority of studies is often from the previous decade. Due to substantial changes in the regulatory landscape, there could be significant changes in the impacts of regulations. If New Jersey's law achieves its intended objec-

[15] Shapiro (2018) emphasized that since most of the policies do not target a specific drug or drug class, it is crucial to examine the effects on the entire set of drugs.

tives, it could have pivotal policy implications, encouraging other states and the federal government to adopt similar restrictions.[16]

The subsequent sections of the paper are structured as follows. Section 2 provides comprehensive information on DTPM and the regulatory landscape of states. Section 3 explains the data. Section 4 outlines the empirical strategy. Section 5 presents the results. Section 6 offers discussions and policy implications. Section 7 concludes the paper.

2 Background

2.1 Physician–Industry Financial Relationships

In 2018, 65% of physicians were recipients of financial disbursements from a total of 1,748 drug companies in the United States.[17] For the purpose of this study, it is essential to categorize industry promotional activities directed towards physicians into two main categories: (1) Detailing and (2) Compensation for Services. Detailing involves face-to-face promotional activities targeted at physicians, typically characterized by frequent interactions of relatively small dollar value. This often includes visits by pharmaceutical representatives to doctors' offices, where they provide information, free samples, meals, and gifts to encourage physicians to prescribe their drugs. According to estimates by Zippia, derived from 30 million job profiles, in 2021, there were approximately 157,000 pharmaceutical representatives employed in the United States. Most drug reps' commissions or bonuses are based on the volume of sales for the targeted drugs in their area (Pharmedout, 2023).[18,19]

The second category under consideration is Compensation for Services, which typ-

[16]The PPSA followed a similar process. Several states enacted disclosure policies, found them effective, and the results convinced lawmakers to adopt a national disclosure policy.

[17]According to the Young et al. (2019) there were 985,026 actively licensed physicians in the United States in 2018. CMS (2019) reported that 632,513 physicians received some kind of remuneration from pharmaceutical firms in the same year. A Simple calculation shows that almost 65% physicians have some kind of relationship with firms.

[18]Full demographics of Pharma reps can be found at: https://www.zippia.com/pharmaceutical-sales-representative-jobs/demographics/

[19]Refer to this article in Washington post about some malpractices employed by pharma to increase the volume of sales: https://www.washingtonpost.com/outlook/i-was-a-drug-rep-i-know-how-pharma-companies-pushed-opioids/2019/11/25/82b1da88-beb9-11e9-9b73-fd3c65ef8f9c_story.html

ically involves consulting arrangements or remuneration for participating as speakers in educational or promotional events. Consulting arrangements are usually formalized through written agreements designed to fulfill specific needs identified by the pharmaceutical industry. On the other hand, speaking engagements often entail inviting physicians to address seminars for other healthcare professionals, focusing on a drug-related topic within the context of continuing education programs or promotional activities. Continuing education programs are typically accredited by The Accreditation Council for Continuing Medical Education (ACCME), with payments not directly disbursed to speakers. In contrast, promotional events lack accreditation, and remunerations are directly provided to the participating healthcare providers. Pharmaceutical companies often target high-prescribing physicians as speakers for such events, leveraging their influence on peers, as noted by Agha and Zeltzer (2022), and covering expenses such as meals and travel reimbursements for speakers and other attendees. The Office of Inspector General (OIG) fraud alert draws attention to specific problematic aspects associated with promotional events. These include lucrative speaker deals, remuneration tied to sales targets, events hosted at entertainment venues or luxury restaurants, and invitations extended to family members or friends of physicians without legitimate reasons for participation.

While some of these practices can clearly conceived as kickbacks, it is essential to avoid generalizing such allegations to all programs or participants. Surprisingly, the existing literature remains inconclusive regarding these interactions' positive and negative implications. This paper aims to contribute novel details and insights, leveraging the comprehensive Open Payments database, to explore all categories of payments.

2.2 States' Regulatory Landscape: NJ vs. Others

Eight states introduced various types of limitations on firm-doctor interactions before the passage of the PPSA. Minnesota, Massachusetts, and Vermont implemented the most comprehensive restrictions, including the disclosure mandates, and banned most gifts. Maine, West Virginia, and the District of Columbia required pharmaceutical firms to disclose some financial transactions with doctors.[20] California and Nevada required pharmaceutical firms to comply with the Pharmaceutical Research and Manufacturers of

[20]Maine updated its regulations in 2019, more details included in the appendix.

America (PhRMA) code of conduct.[21] Moreover, between 2006 and 2012, several medical centers across the United States banned and restricted sales visits by pharmaceutical sales representatives (Larkin et al., 2017).

New Jersey law is the first of its kind, according to (Sullivan, 2018), and it is unique in several aspects. First, since its implementation came long after the passage of the PPSA, it allows for the utilization of the resulting rich transfer data to analyze the trends before and after the policy and assess how regulations affect different types of DTPM and prescription patterns. Second, while all other rules hold manufacturers responsible for violations, New Jersey's rule applies directly to doctors. Third, it has a stringent set of regulations on almost all categories of payments, from capping small payments for lunches and dinners to larger payments for bona fide services like consulting and speaking at promotional activities.[22] Fourth, New Jersey is the only state that imposes tight restrictions on doctors' income and caps the total benefits they can receive from pharmaceutical firms.

On January 16, 2018, New Jersey's new regulations "limiting gifts and payments from prescription drug and biologics manufacturers to prescribers" became effective.[23] Here is a part of NJ Governor Chris Christie's statement on Sept 1, 2017:

> *"While the vast majority of doctors care for their patients honorably and professionally, their education about many of the drugs they are prescribing comes too often from pharmaceutical sales people, who may not always provide an objective analysis of the human and social impacts the drugs may have. This rule will help us address any concerns about whether treatment decisions of prescribers are being improperly influenced."*

The general prohibitions in the regulations include the following:

1. Meals with a market value larger than $15.[24]

2. Any financial benefit or benefit in kind.

[21] See the appendix for details about each state's regulations.

[22] According to the policy, bona fide services means those services provided by a prescriber pursuant to an arrangement formalized in a written agreement including, but not limited to, presentations as speakers at promotional activities and education events, participation on advisory boards, and consulting arrangements.

[23] The law's text can be found here: https://www.njconsumeraffairs.gov/regulations/Chapter-45J-Prescriber-Compensation.pdf

[24] As an amendment in 2019, the attorney general permitted the meal limit to raise by one dollar increment according to the Consumer Price Index (CPI) and raised the limit for dinners to $30.

3. Any entertainment or recreational items.

4. Any item of value that does not advance disease or treatment education.

5. Aggregate value of payments for bona fide services should not exceed $10,000 in aggregate in any calendar year from all pharmaceutical manufacturers.[25]

The rule applies to physicians with an active NJ license who either practice in NJ or have NJ patients.[26] Educational events, medical devices, contracts made before Jan 15, 2018, and firms' employees are exempted.[27] The law does not provide for penalties against pharmaceutical manufacturers for violations. Instead, enforcement will rest with the prescribers' respective licensing boards, which will have the authority to impose disciplinary action and/or civil penalties. This is unprecedented and different from all other laws that penalize pharmaceutical firms.

3 Data

3.1 Open Payments

The first data source is Open Payments, a public database organized by CMS that contains detailed data on all industry payments made to physicians.[28] I observe detailed information about the type, dollar value, and frequency of payments, doctors' and firms' IDs, drugs' names, and the exact payment date. CMS publishes the data annually in three separate categories: 1) General Payments, 2) Research Payments, and 3) Ownership and Investment Interests.[29] The focus of this study is on general payments, which have 16 different categories from which only six categories should be affected by policy

[25]Payments for speaking at education events, research activities, royalties, and licensing fees are not subject to this cap, but must be for fair market values and outlined in a written agreement.

[26]This implies that doctors without New Jersey license who practice in New York and Pennsylvania near the New Jersey borders are not affected by the policy. It is possible for doctors to hold licenses from multiple states. Therefore, a small group of physicians with New Jersey licenses who practice in New York or Pennsylvania was removed from the data to avoid concerns regarding spillover effects.

[27]The regulations have several exemptions; details of limitations are outlined in the appendix.

[28]There are some exceptions. First, companies must report payments only if they surpass $10 during a specific interaction or if the cumulative value throughout a calendar year exceeds $100. Nevertheless, to ensure compliance with the cumulative $100 reporting threshold, companies frequently monitor and report payments that are less than $10. Second, some pharmaceutical reps might leave free samples or other advertising materials for doctors; these payments are not reported to CMS.

[29]All of the marketing activities are included in the general payment category, so two other categories are not the focus of this study.

and are included in the analyses.[30] Table 1 provides the proportion of each category relative to the total values in terms of dollar values and frequency along with mean and median for the dollar value of payments. The third column indicates the percentage of physicians nationwide receiving at least one payment from 2014 to 2019 in each category. The payments are mutually inclusive, so the percentages are not expected to sum to a hundred. Overall, the pharmaceutical industry paid 42.6 million payments worth 3.63 billion dollars to 735,462 physicians nationwide between 2014 and 2019 with the mean and median of $1,527 and $119.6, respectively. Compensations for services other than consulting, while only paid to 5% of physicians, dominate others and account for more than 50 percent of the dollar value of payments.[31] Food and beverages consist of about 94 percent of payments in terms of frequency, and almost all doctors in the sample received at least one payment between 2014 and 2019.

3.2 Medicare Part D

The second series of datasets are the Medicare annual Part D databases. These datasets are based on claims submitted by each physician and healthcare provider to Medicare for each prescribed drug, aggregated by provider and by provider and drug. Oeverall, the Medicare part D dataset contains records associated with 114,419 physicians and 3,213 distinct part D drugs for 2014-2019 in NJ and neighboring states of NY and PA. For each doctor-drug-year combination, the data includes the National Provider Identifier (NPI) of the prescriber, medical specialties, total number of claims, total number of patients, total days' supply, and total drug cost.[32,33] While the aggregated number of claims by branded or generic status is observable in the provider-level data, the drug-level data does not distinguish between generic and branded status.[34] Additionally, I cannot differentiate

[30]The definitions for each of these categories are included in the appendix. Some categories like education, grant, and ... are excluded because they are mainly related to research and education. Others, like entertainment or gifts, are also excluded because they are scattered, and a cohesive argument cannot be made for them.

[31]This category is mentioned in the OIG fraud alert as the category of concern.

[32]I also incorporate the average beneficiary risk score for each physician. This metric serves as a proxy for the overall health status of a doctor's patient population. Medicare calculates these risk scores based on various patient-specific risk factors. [Insert link to definitions here] A higher average risk score indicates that a physician's patient population generally has more severe health conditions or is at greater risk for adverse health outcomes.

[33]Detailed explanation for each outcome is included in the appendix.

[34]Since the drug-level data does not distinguish between branded or generic status, I use the physician-level data to conduct the brand-generic analysis. The total number of branded or generic claims is used

between different dosage strengths of an identical drug (e.g., 50mg, 100mg) or forms of the drugs (e.g., injectable, oral). The data are reported if the annual number of claims for each drug exceeds 10 claims.[35]

The prescription and payment datasets are merged using National Provider Identification numbers, year, and drug names. The dataset is rectangularized to include an observation for each physician-drug combination over the six years. The resulting dataset comprises 529,027 observations associated with 9,959 physicians and 549 distinct drugs over the sample period. Table 2 reports the overall number of drugs and physicians, along with the average values of outcomes for each drug each year, separately for NJ (treated state) and NY and PA (control states) for the sample period (2014-2019).

4 Empirical Strategy

The empirical strategy seeks to compare changes in DTPM and prescribing behavior among New Jersey doctors to their similar peers in neighboring states of NY and PA before and after the policy. This is estimated using a difference-in-difference event study design with matching, tracking outcomes before and after the policy relative to the time preceding its implementation. For physicians p, drug d, and time period t, I estimate the event-study specification:

$$Y_{pdt} = NJ \times \sum_{r \neq 2017} \beta_r I(r) + \beta_{pd} + \beta_{td} + \epsilon_{pdt} \tag{1}$$

In the first stage analysis, the primary outcomes, Y_{pdt}, are the dollar value and frequency of industry payments received by each physician for each drug-year. For the reduced form estimations, the primary outcomes are total claims submitted to Medicare, number of patients, total days supply, and total expenditures for a physician-drug-year. NJ is an indicator variable, taking a value of 1 if the doctors are licensed in NJ and 0

as a proxy for prescription volume, with the caveat that the exact number of prescriptions in each claim is not observable. The reported numbers in table 2 are based on this final dataset.

[35] A limitation of this dataset is that drug information is excluded if the number of claims is less than 11, to protect patient privacy. To address this issue and ensure that this limitation does not significantly affect the estimates, the main analysis is conducted using data from physicians for whom 95% of their prescriptions can be observed during the pre-policy years (2014-2017). Various robustness checks were performed, and the results indicate that the effect is not driven by specific sample selection and is consistent across all samples. More details can be found in the appendix.

otherwise. $I(r)$ represents the event time indicator, with 2017 as the omitted reference time. Therefore, each estimate of β_r measures the changes in outcomes in NJ compared to neighbouring states during event time r, as measured from the year prior to the policy. The fixed effect β_{pd} allows a different intercept for each physician-drug combinations. β_{td} controls for changes in prescriptions of each drug over time, including direct-to-consumer advertising. If payments and prescribing patterns were trending in parallel before the policy, I expect that estimates prior to 2018 will not be significantly different from zero. In addition to event study estimates, I also report the difference-in-difference (DID) estimates. The same equation is used for estimation except that the indicator variables for each event-time are replaced with a single dummy ($NJ \times Post$) denoting the NJ in post-policy periods.

While difference-in-differences design does not require treated and control physicians to be similar in levels, I conducted matching on several variables using pre-policy data to ensure a rigorous comparison. I employed a combination of exact and distance matching to pair doctors in the pre-policy period. Specifically, I implemented exact matching on medical specialty and distance matching on average beneficiary risk scores, dollar value and frequency of industry payments, number of distinct drugs prescribed, and total number of patients per physician in the pre-policy period.[36]

I utilized the optimal full matching approach developed by (Hansen, 2004; Hansen and Klopfer, 2006). Full matching is a type of subclassification where all observations are assigned to a subclass and receive at least one match, with distances minimized within each subclass (Stuart et al., 2011). The advantage of full matching is that no observations are discarded, and it achieves better balance than other matching algorithms.[37] Doctors were assigned to subclasses based on their exact specialty, dollar value and frequency of industry payments, number of distinct drugs prescribed, total number of patients, and their beneficiaries' average risk scores (as a proxy for their patients' conditions) during each year of the pre-treatment period (2014-2017). The resulting matching weights were then used in regression analysis, ensuring comparison of doctors with similar specialties,

[36]The matching procedure enhances the validity of comparison. Multiple robustness checks demonstrate that the results remain consistent regardless of matching. Please refer to the appendix.

[37]The selection of optimal full matching was based on a comprehensive review of matching literature and empirical testing of various algorithms. This method consistently outperformed alternatives in achieving covariate balance while retaining all observations in the sample.

levels of exposure to pharmaceutical companies' promotions, number of drugs and patients, and patient populations for each year during the pre-treatment period. Detailed discussion about the matching process is provided in the appendix.

5 Results

5.1 Direct-to-Physician Marketing

The first stage analysis examines the effect of the policy on the dollar value (i.e. intensive margin) and frequency (i.e. extensive margin) of industry payments to prescribers with New Jersey license relative to their peers in the neighboring states of New York and Pennsylvania. The sample consists of industry payments to 31,446 unique physicians and total of 4,359,666 observations for marketed drugs across 6 years. The results indicate that the dollar value and frequency of industry payments directed toward NJ physicians were significantly reduced compared to their peers in NY and PA after policy implementation. As this average effect might mask important information about which categories of payments are mostly affected by the policy, I also report the effect of the policy separately for each category.[38]

The event study figures and difference-in-difference estimates of the effects of the policy on the total dollar value and frequency of industry payments are presented in Figures 1 and 2 and the first column of Table 3. Figure 1 indicates a large and consistent reduction in the dollar value of industry payments to physicians in New Jersey after the policy implementation compared to their peers in New York and Pennsylvania. Specifically, each doctor in New Jersey received $22 less per drug per year post-policy, representing a 27% reduction from the pre-policy mean of $83.7. This reduction in dollar value is consistent and remains relatively stable throughout the post-policy periods. Figure 2 illustrates the effect of the policy on the frequency of industry payments. The total reduction in frequency of industry payments is small, at about 3% of the sample mean [39]. This pattern is primarily due to the dominance of food payments in the total number of payments. As explained in Section 2.2, while the dollar value of meal payments was

[38]There are 16 categories of marketing in open payment and based on the regulations, I identified six categories that should be affected by the regulations.

[39]Frequency of payments are multiplied by 1000 to enhance readability.

capped by the policy, the frequency of food payments was not restricted. This distinction becomes evident when examining the breakdown of overall numbers by category.

Figures 3 and 4 and columns 2-7 of Table 3 exhibit the effect of the policy on different categories of the industry payments. As explained in Section 2.1, some payment categories, such as compensation for services, are typically substantial but less frequent, while others, like food payments, are smaller in value but more widespread. The payments for travel are also often linked to speaker programs. The primary driver of the reduction in both the dollar value and frequency of industry payments is the "compensation other" category, which mainly consists of promotional speaking engagements. Panel A of Table 4 further highlights the policy's impact, showing a reduction of \$14 (a 30% decrease from the pre-policy mean) for "compensation other," \$6 for food (32%), and \$1.5 for travel (21.4%). While the policy effects for compensation and travel remain consistent across both years after the policy, the dollar value of food payments rebounded after a year. This rebound is primarily due to a 2019 amendment that allowed meal payments for dinner to increase to \$30. Regarding the frequency of industry payments, the reductions are most pronounced in "compensation other" (29%), consulting (13%), and travel (23%). As previously mentioned, the reduction in the frequency of food payments is not significant and rebounded after a year, contributing to the overall pattern observed in total frequency of payments.

Overall, the first stage results confirm a substantial effect of the policy on the volume of marketing activities directed toward physicians with NJ license. The main driving force of the reduction in both dollar value and frequency is the "compensation other" category, which mainly consists of promotional speaking payments. These payments were subject of the recent OIG fraud report Office of Inspector General and Human Services (2020) and are usually made to key opinion leaders to leverage their influence over their peers Agha and Zeltzer (2022).

5.2 Physicians' Prescribing Behavior

The previous section indicates that the restrictive policy in New Jersey (NJ) substantially reduced the marketing activities directed toward physicians with NJ licenses. This result leads us to the next stage of the analysis, which examines the effect of the policy on pre-

scribing behavior. Numerous studies in the literature have found that industry payments increase the prescribing rates and expenditures of the marketed drugs.[40] In this section, I shed light on whether the restrictive policies are able to affect prescribing behavior. The policy reduced industry payments to physicians in NJ, raising the important question of whether doctors with NJ license with similar characteristics of their peers in NY and PA reduced their prescription volumes of marketed drugs due to fewer exposures to pharmaceutical promotions.

The reduced form analysis addresses this question by examining the effect of the policy on prescribing behavior. Industry payment data were linked to Medicare's Part D prescriber data using each physician's National Provider Identifier (NPI) and drug names, resulting in 532,192 observations and 9,934 physicians. Following various studies in the literature, the main outcomes used for assessing prescription volumes are physicians' number of patients, the number of claims submitted to Medicare, and the total days' supply for each drug annually. While the number of patients and claims can be perceived as the extensive margins of prescription volume, the total days' supply represents the intensive margin (e.g., patients are prescribed more frequent dosing or are filling their prescriptions more regularly). Overall, physicians in NJ received lower dollar values of industry payments and reduced their prescription volume of marketed drugs across both extensive and intensive margins. Although the reduction in total drug costs is marginally significant, it is not the primary focus of this study. [41]

Figure 5 shows the impact of the policy on industry payments and prescribing behavior. The event study figures reveal no significant pre-policy differences in various outcomes between physicians in NJ and their counterparts in New York (NY) and Pennsylvania (PA). However, post-policy, there is a substantial reduction in both the dollar value and frequency of payments, as well as in prescription volumes. Columns 1 and 2 of Table 4 report the difference-in-difference estimates along with the event study estimates for the effect of policy on industry payments. The industry payments directed to NJ doctors experienced a reduction of 21% from the pre-policy mean of $298.27. As

[40] Refer to section 1 for the list of these studies.

[41] The measure of drug cost reported in Medicare's Part D dataset is closest to list prices. It includes the expenditures by patients, third-party payers, and insurance plans. Therefore, a clear breakdown of these expenditures cannot be made. Moreover, this measure does not reflect post-market rebates paid from drug firms back to insurers or pharmacy benefit managers.

explained in the first stage analysis, while the event study estimates show a substantial reduction in the frequency of industry payments in 2018, the overall number of payments did not significantly decrease, as the overall number of payments is dominated by food payments.[42]

Columns 3-6 of table 4 report the difference-in-difference estimates along with the event study estimates for the effect of policy on prescribing behavior. The policy reduced the prescription volumes of marketed drugs consistently across both extensive and intensive margins. The results indicate that after the policy implementation, NJ physicians submitted about three fewer claims for each drug annually to Medicare (6.8% over the pre-policy mean of 44.49). The unique number of patients for each drug also experienced a reduction of 0.6682 (5.6% over the pre-policy mean of 11.92). The total days' supply for each drug also reduced by 99.7 (5.9% over the pre-policy mean of 1,687). While only significant at the 10% level, the reduction in expenditure on marketed drugs shows a relative decline of $1,288 (5% over the mean).

Overall, the policy substantially reduced the prescription volume of marketed drugs in NJ compared to the neighboring states of NY and PA. It is important to note that the comparison is done using matching on all important characteristics. The doctors have identical medical specialties, similar numbers of distinct drugs prescribed, similar baseline levels of exposure to pharmaceutical promotions, and similar numbers of patients. The matching also controls for each physician's patient population using beneficiary average risk scores, which account for various demographic variables, pre-existing conditions, and the severity of diseases.

5.3 Heavy Receivers

An interesting question that arises in the context of this study pertains to the characteristics of the doctors who are subject to heavy pharmaceutical promotions and whether the policy disproportionately affects these doctors. Focusing on this group of physicians is important for two main reasons. First, several studies have shown that pharmaceutical companies regularly monitor physicians' prescribing behaviors and often target those who prescribe large volumes of drugs (Fugh-Berman and Ahari, 2007; Fugh-Berman, 2008;

[42]The logic follows my explanation in Section 5.1.

Carey et al., 2021). These companies frequently invite such doctors to speak about their products to other healthcare professionals, leveraging their influence over their peers. Therefore, restricting their exposure to pharma promotions could yield significant direct and indirect benefits (Agha and Zeltzer, 2022). Second, due to their large prescription volumes and extensive patient interactions, any benefits resulting from imposing these limitations on this group would likely have a more pronounced impact on patient outcomes and healthcare spending.

To address this question, I identify 497 physicians who receive the largest amounts of payments from the drug industry (i.e., the top 5% of doctors) between 2014 and 2017 in NJ, NY, and PA. On average, these doctors received $42,085 annually. The median doctor in this group received an average of $27,531 per year from the pharmaceutical industry. The top five medical specialties targeted by pharma promotions were Cardiologists (20%), Neurologists (14%), Endocrinologists (13%), Internal Medicine physicians (9%), and Psychiatrists (6%). Comparing pre-policy averages in Table 5 with those in Table 4, it becomes evident that this group of doctors received substantially higher amounts of industry payments compared to the average figures—approximately 10 times more in dollar value and 4 times more in frequency. They also issued significantly more prescriptions compared to average doctors, consistent with the findings in the literature that pharma promotions disproportionately target heavy prescribers (Fugh-Berman and Ahari, 2007; Fugh-Berman, 2008; Carey et al., 2021).

The DiD estimates reported in Table 5 show that these doctors received, on average, $644 less per drug after the policy—almost 10 times the reduction seen for other doctors. This represents a 20% decrease from the pre-policy mean, which is proportionally similar to the reduction observed in Table 4. Additionally, the policy reduced the frequency of industry payments by 10.5% for this group, a significantly larger decrease compared to the average doctors. This reduction was primarily driven by decreased payments for speaker programs, as highlighted in the first-stage analysis. Additionally, the policy resulted in an approximate 10% reduction in prescription volume for these doctors, nearly double the reduction observed previously. These findings indicate that the policy significantly reduced exposure to pharmaceutical promotions for this group, which could potentially improve patient outcomes and lessen adverse effects stemming from peer influence.

5.4 Placebo Analysis with Never Receivers

A critical assumption for a valid DiD design is the absence of any co-occurring shocks in New Jersey in 2018 that could independently cause a reduction in industry payments, prescription volumes, or drug costs. To ensure this assumption holds in our study, I implemented two approaches.

First, I conducted a review of regulations in New Jersey and the neighboring states of New York and Pennsylvania. This review revealed no specific regulatory changes around 2018 that would differentially impact pharmaceutical promotions or prescription volumes in New Jersey compared to New York and Pennsylvania. Second, while this assumption is not directly testable, a placebo test using the same set of drugs prescribed by doctors without engagement with drug firms can help alleviate concerns. The underlying assumption is that if external shocks uniquely affected drugs or prescribers in New Jersey, we would observe changes in the prescribing volume of non-recipients as well. [43]

Table 6 reports the DID estimates for the placebo observations (i.e., the same set of drugs prescribed by doctors without any associated payments from the drug industry) alongside the actual estimates. Two interesting patterns emerge. First, none of the placebo estimates are significant at the 5% level, and the estimates for the number of patients and total claims (i.e., the extensive margin of prescription) exhibit different signs. Second, despite using the same set of drugs for the placebo analysis, the pre-policy averages are lower for doctors without engagement with drug firms. This is consistent with the findings in the literature, indicating that the pharmaceutical industry actively monitors physicians' prescribing behavior and typically targets doctors with high prescription volumes (Fugh-Berman and Ahari, 2007; Fugh-Berman, 2008; Carey et al., 2021).

5.5 Branded vs. Generic Prescribing

According to the FDA, a brand-name drug is a medication marketed under a proprietary, trademark-protected name. Conversely, a generic drug is identical to a brand-name drug in dosage, safety, strength, administration, quality, performance, and intended use but benefits from vibrant competition, resulting in significantly lower prices (FDA, 2023). In

[43] The only possibility that invalidates this claim is the existence of other characteristics that are correlated with the receipt of industry payments.

2018, generic prescriptions accounted for 90% of all prescriptions but only constituted 22% of the overall cost, which has been estimated to save the US healthcare system $293 billion (AAM, 2019). Almost all industry promotions focus on brand-name drugs, posing a significant barrier to physicians' adoption of cost-saving generic alternatives, which could potentially save millions of dollars annually for patients and the US healthcare system (Datta and Dave, 2017; Park, 2024). Engelberg et al. (2014) found that exposure to pharmaceutical promotions increases the likelihood of brand-name drug prescriptions. One critical question is whether restrictive policies, such as those implemented in New Jersey, facilitate the transition from branded to generic prescribing. In this section, I utilize physician-level data from Medicare Part D to examine whether the restrictive policy in New Jersey has facilitated a shift from branded to generic prescribing.

For brand-generic analysis, since the physician-drug-level data is not available, the analysis is conducted using physician-level data. The following specification is used to conduct the analysis:

$$Y_{pt} = NJ \times \sum_{r \neq 2017} \beta_r I(r) + \beta_p + \beta_t + \epsilon_{pt} \tag{2}$$

The primary outcomes, Y_{pt}, are proportions of brand and generic claims and costs by each doctor. β_p and β_t are doctor and time fixed effects.[44]

As evidenced in Figure 7, physicians in New Jersey (NJ) and their counterparts in New York (NY) and Pennsylvania (PA) exhibited similar trends before the policy implementation in terms of the total dollar value received from the industry, the frequency of payments, the proportion of brand-generic claims, and costs. However, once the policy was adopted in 2018, NJ physicians received fewer payments with lower dollar values, reduced their proportion of brand prescriptions, and transitioned to more generic prescribing. Consequently, the proportion of brand-name drug costs decreased, while the proportion of generic drug costs increased by similar proportions.

The Difference-in-Differences (DID) and event study estimates are presented in Table 7. The results indicate a 0.66 percentage point (p.p.) reduction in the volume of brand claims submitted to Medicare by NJ doctors and a 0.77 p.p. increase in generic claims

[44]The number of claims is the only outcome reported in doctor-level data by generic and brand status and is used as the proxy for prescription volume.

following the policy implementation. Correspondingly, there is a reduction of about 1.55 p.p. in the proportion of brand-name drug costs and an increase of 1.64 p.p. in generic drug costs.

The pre-policy averages show that, while brand-name claims constituted approximately 20% of overall claims, the costs associated with them accounted for 53% of overall costs, reaffirming the significant cost-saving implications of the transition to generic prescribing. The regulations in NJ led to a 1.55 p.p. decrease in expenditure on brand-name drugs per doctor annually, accompanied by a corresponding 1.64 p.p. increase in expenditures on generic drugs. Assuming the findings of this study are generalizable, considering the pre-policy average annual costs of \$160,428 for brand-name drugs and \$45,137 for generic drugs per NJ doctor, a straightforward calculation yields a \$1,728 reduction ((0.0164 $\times$ \$45,137) – (0.0155 $\times$ \$160,428)) in total expenditure per doctor-year in NJ compared to their peers in NY and PA.

6 Heterogeneous Treatment Effects

The Average Treatment on the Treated Effects (ATT) presented in section 5 mask important information regarding which groups of doctors and drugs are the most sensitive to the policy. Identifying group-specific effects not only helps in directing more targeted policies for the future but also sheds light on potential mechanisms. Therefore, I conducted two heterogeneity analyses to investigate the potential mechanisms underlying the observed average effects.

The first set of analyses is based on the average dollar value of payments received by doctors during the pre-policy period. This analysis is crucial as it reveals whether the policy disproportionately affects doctors with high levels of exposure to pharmaceutical payments. Each physician was assigned to one of four bins based on the quartiles of payments received in the pre-policy period. Table 8 shows the distribution of payments, corresponding bin cutoffs, and the number of doctors in each assigned group.

Figure 8 presents the estimates separately for each group. To ensure comparability of estimates across groups, the outcome variables are scaled by their pre-policy averages. The results indicate that the dollar value of payments reduced for all groups except

doctors in the first quartile of payments, and the frequency of industry payments predominantly decreased for doctors in the second quartile. The changes in prescribing behavior are also primarily attributable to doctors in the top three quartiles. [45]

These findings reveal several important facts. First, the policy does not affect prescribers whose exposure to pharmaceutical promotions is minimal (e.g., those in the first quartile), which can also be seen as a kind of placebo test similar to the analysis in Section 5.3. Second, the changes in payments and prescribing behavior are mainly coming from doctors with high exposure to pharma promotions, consistent with the results in Section 5.2. [46]

The second important dimension of heterogeneity is based on the age of drugs at the time of the policy implementation.[47] This aspect of heterogeneity could shed light on two important potential mechanisms. First, as explained in the introduction, the pharmaceutical industry claims that payments are purely informational and are not intended to affect prescribing behavior. If this claim is true, we should observe that the resulting average reduction in prescription volumes is coming purely from the newest drugs with no effect on older drugs. Second, I can use the 5-year FDA exclusivity cutoff, which is provided for branded drugs to protect them from generic entry, to observe whether the reduction is coming from drugs with generic alternatives and connect the drug-level analysis to the brand-generic analysis. As a transition to generic alternatives was observed in section 5.4, the reduction in prescription volume should be coming at least partially from drugs with generic alternatives.[48]

The median age of the drugs in the sample is 8 years, with a mean of 9.5 years. Table 9 reports the summary statistics for drugs based on the FDA exclusivity cutoff during the pre-policy years. Out of 528,192 observations, only 116,596 are for drugs younger than 5

[45]The standard errors are larger for the doctors who receive payments greater than 500$ due to the very large payments for some physicians.

[46]One important point to note is that the possibility of spillover effects should not be neglected in this analysis. As the largest proportion of reduction in payments stems from physicians with high exposure to pharma promotions, and it was shown in Section 5.1 that these groups mainly consist of physicians with a high level of influence over their peers, some of the reduction in lower quartiles might be indirectly attributable to heavy receivers.

[47]Drug companies cannot advertise a drug before FDA approval. Therefore, I obtained drugs' approval year from the FDA database and subtracted them from the policy year (i.e., 2018) to calculate drugs' age.

[48]It is not easy to comment on whether a specific drug has a generic alternative or not, as some drugs can be used to treat or alleviate multiple diseases.

years, accounting for approximately 22% of the observations. Overall, only 37% and 25% of industry payments, in terms of dollar value and frequency respectively, are made for drugs within the exclusivity period, with the overwhelming majority of payments directed toward older drugs. This could indicate that information transmission might not be the sole objective of pharmaceutical promotions. In addition to summary statistics, figure 9 reports the effect of policy on different drugs based on the 5-year FDA exclusivity cutoff. The results indicate that the average 6% reduction in prescription volumes is proportionally the same for older and newer drugs and does not come purely from the newest drugs. This might suggest that the claims made by pharmaceutical companies about the purely informational nature of the DTPM may not be true. Moreover, some older drugs with generic alternatives might be the driving force behind the transition observed in section 5.4. [49]

7 Discussions and Policy Implications

The financial relationship between pharmaceutical firms and physicians cannot and should not be completely eliminated due to the interconnected nature of their work. Pharmaceutical companies need to seek advice from physicians who are experts in their fields to develop and improve their products. Physicians, in turn, need to stay informed about the development of new pharmaceutical products. The main focus when designing restrictive policies should be regulating the problematic aspects of these interactions that are not related to research and are solely for promotional purposes. Here, I shed some light on the current debate and highlight some problematic aspects of these interactions.

The efficacy of restrictive policies in reducing direct-to-physician marketing (DTPM) and influencing prescribing behavior has been the center of debate over the past two decades. Financial relationships between physicians and pharmaceutical companies can create potential conflicts of interest and incentivize doctors to prescribe specific drugs. While it is challenging to definitively determine whether industry payments serve as informational resources or tools to influence prescription behavior, most studies in the literature support the latter. Concerns over these interactions led policymakers to intro-

[49] To ensure that DID estimates are not driven by differential pre-trend across groups, the event study figures for all estimates are reported in the appendix.

duce the Physician Payments Sunshine Act in 2013 as part of the Affordable Care Act (ACA), mandating that all pharmaceutical payments be reported for public disclosure. Similar concerns have prompted several medical school systems to ban most of these interactions (Larkin et al., 2017). The results of this study also indicate that these financial relationships may not be purely informational.

Another aspect of the problem is physicians' underestimation of the influence of pharmaceutical promotions (Grundy et al., 2013; Anderson et al., 2009; Steinman et al., 2001; McKinney et al., 1990; Dana and Loewenstein, 2003). Reports from former pharmaceutical representatives suggest that companies use sophisticated marketing and data mining techniques to identify vulnerable physicians and influence their prescribing behavior. They distribute funds, gain access to prescription data, and track the prescription patterns of particular doctors with whom they hold meetings (Fugh-Berman and Ahari, 2007; Fugh-Berman, 2008). They tend to target physicians who are shown to be sensitive to detailing activities. While patient information is usually removed to maintain confidentiality, there is a need to regulate how pharmaceutical companies can access physicians' information and their prescribing habits.[50]

The most concerning aspect of these interactions appears to be promotional speaker programs, where key opinion leaders are invited to speak to other healthcare professionals about specific drugs or products. These programs are usually designed to leverage the peer influence of key opinion leaders. The agenda and presentation slides are typically prepared by the pharmaceutical companies. Recent reports from the Office of Inspector General (OIG) have raised concerns about these programs, and authorities have expressed doubts about the current design and informational purposes behind such events (Office of Inspector General and Human Services, 2020). Future policies should focus more on regulating this channel of influence, as they constitute a substantial portion of the overall dollar value of payments.

From a cost-saving perspective, these restrictive policies could also be beneficial. Companies that produce generic drugs usually do not have the resources to spend as much on DTPM as branded drug companies do. Even if these interactions are purely

[50]Refer to this article in Washington post about some malpractices employed by pharma to increase the volume of sales: https://www.washingtonpost.com/outlook/i-was-a-drug-rep-i-know-how-pharma-companies-pushed-opioids/2019/11/25/82b1da88-beb9-11e9-9b73-fd3c65ef8f9c_story.html

informational, they are skewed toward branded drugs. This results in DTPM functioning as a barrier to transitioning from branded to generic drugs, potentially costing the US economy billions of dollars. There is a need for new regulations and financial resources to enhance and update physicians' education about generic alternatives to expensive branded drugs.[51].

8 Conclusion

In this paper, I evaluate the impact of a unique restrictive policy implemented in New Jersey on direct-to-physician marketing (DTPM) and physicians' prescribing behavior. The results show that physicians with New Jersey licenses became less exposed to pharmaceutical promotions and reduced the prescription of marketed drugs after the policy, compared to their colleagues in New York and Pennsylvania. The main channel of payment affected by the policy is promotional speaking events. Additionally, the policy appears to facilitate the transition to generic prescribing among New Jersey prescribers. Although there are no observable changes in the prescribing behavior of physicians with no or limited exposure to pharmaceutical promotions, the results indicate that physicians with a high level of interaction tend to be more responsive to the restrictive policy and reduced their prescription volume substantially. Finally, there is no discernible difference between the effect of the policy on the prescribing behavior of new and old drugs, supporting the hypothesis that pharmaceutical promotions may not be purely informational.

[51]Refer to section 5.5 for a more detailed discussion.

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Figure 1: Effect of Policy on Dollar Value of Industry Payments

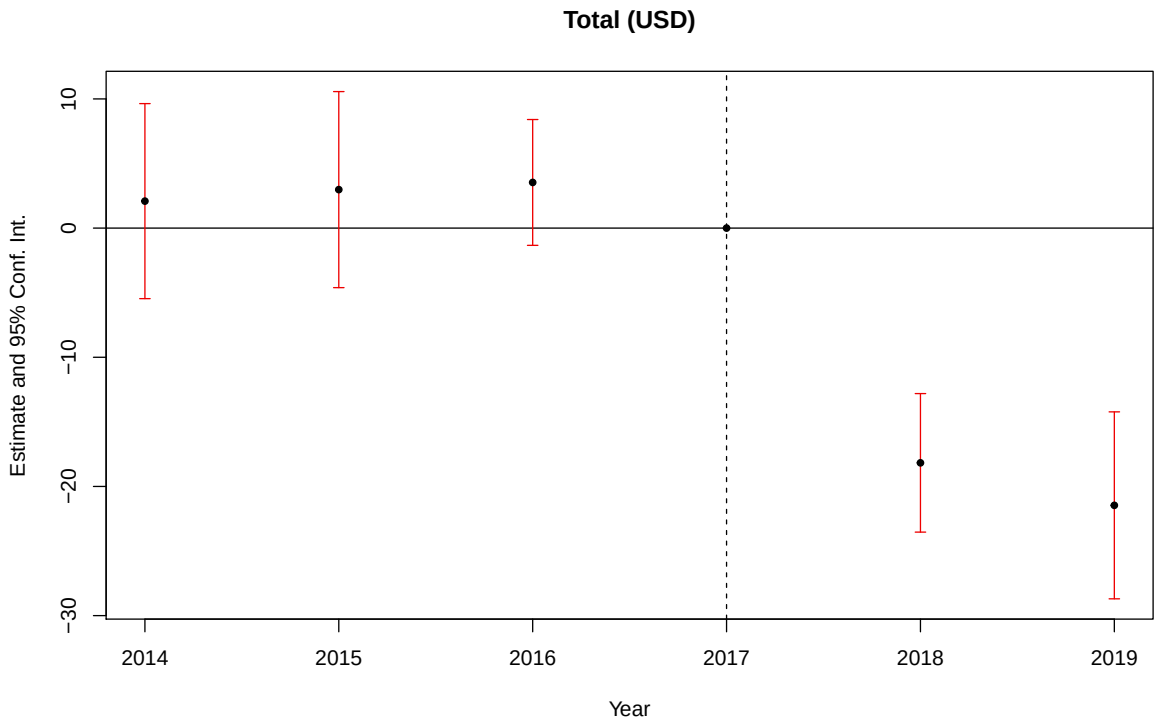
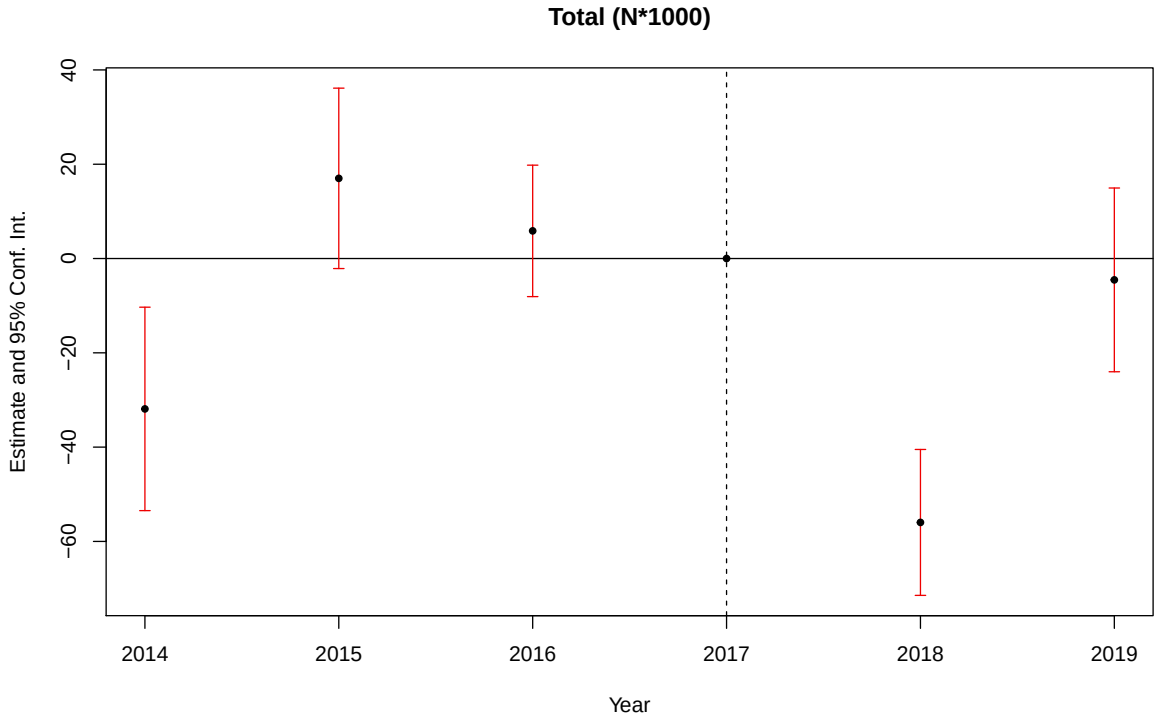


Figure 2: Effect of Policy on Frequency of Industry Payments



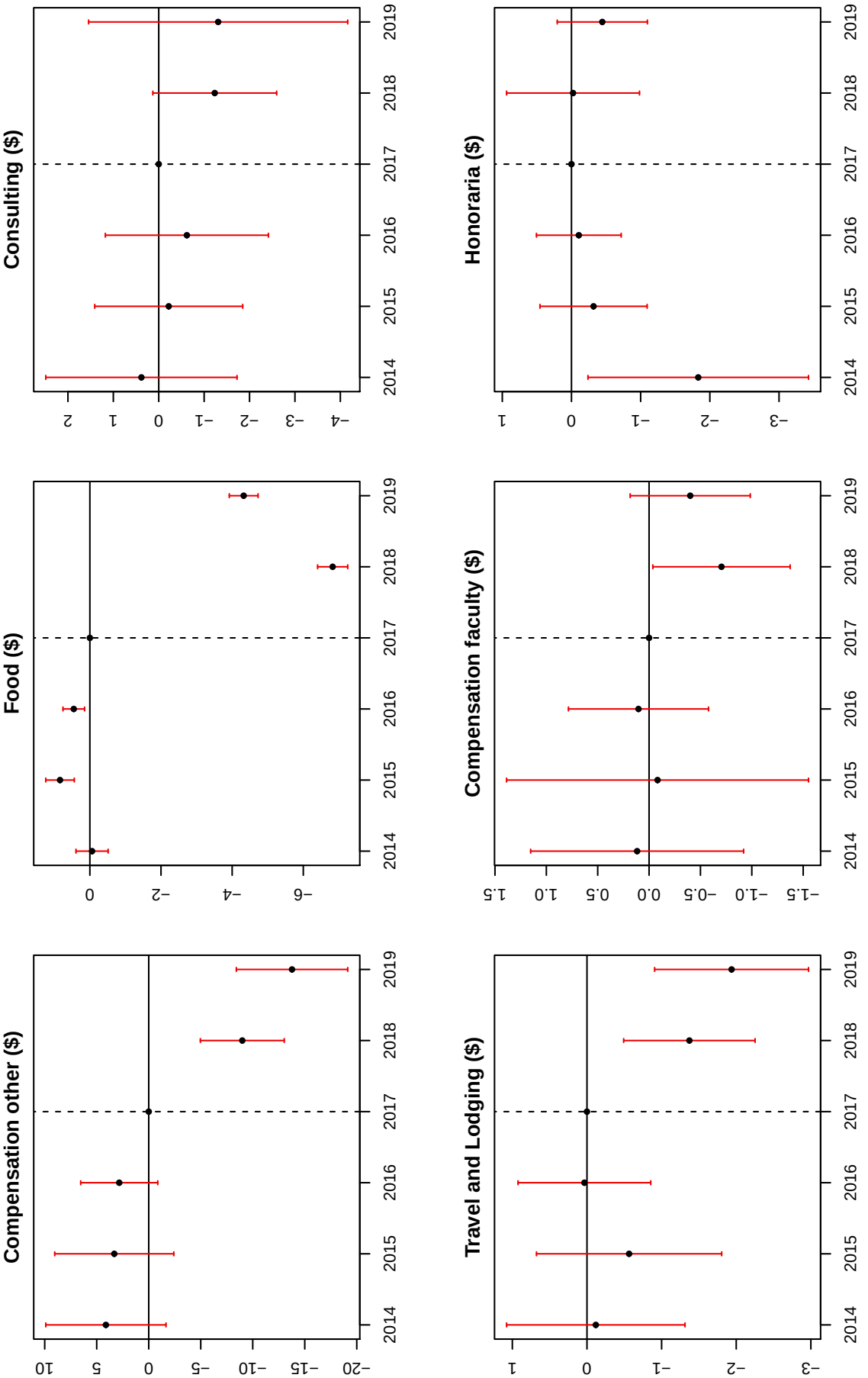


Figure 3: Effect of Policy on Dollar Value of Each Category of Industry Payments

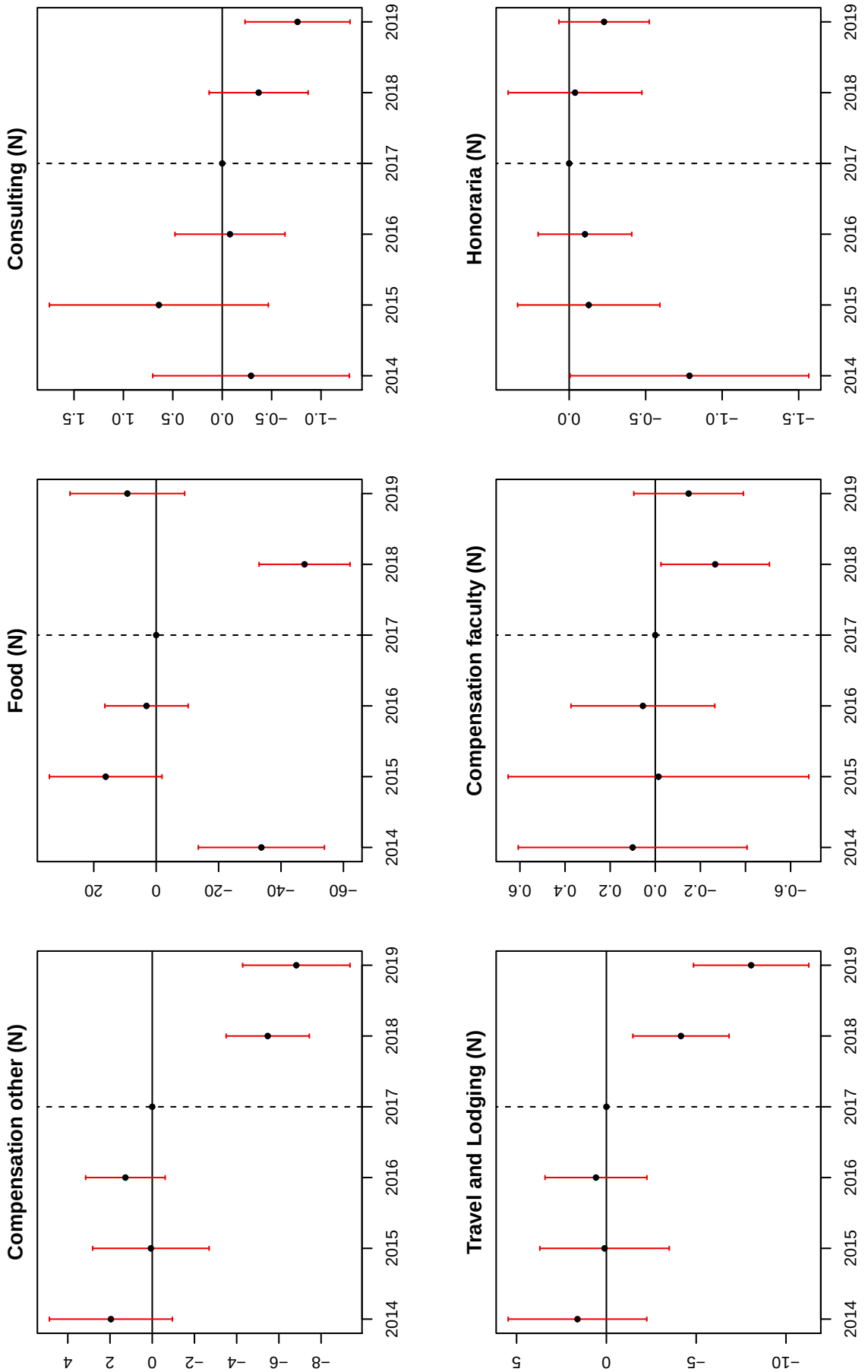


Figure 4: Effect of Policy on Frequency of Each Category of Industry Payments

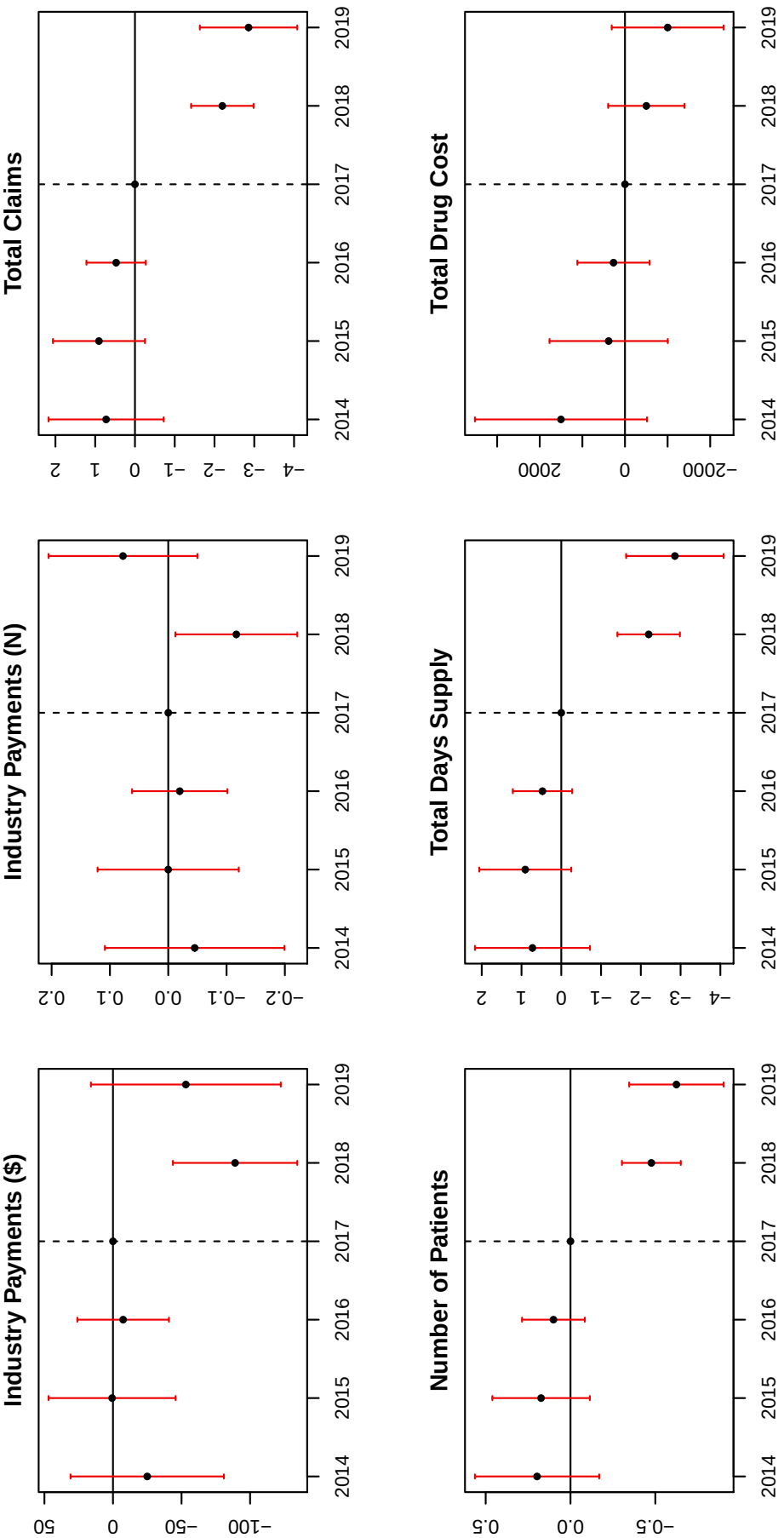


Figure 5: Effect of Policy on Industry Payments, Prescriptions Volume and Cost

Figure 6: Effect of Policy on Industry Payments, Prescriptions Volume and Cost for Heavy Receivers

Figure 7: Effect of Policy on Industry Payments and Brand Vs. Generic Prescribing

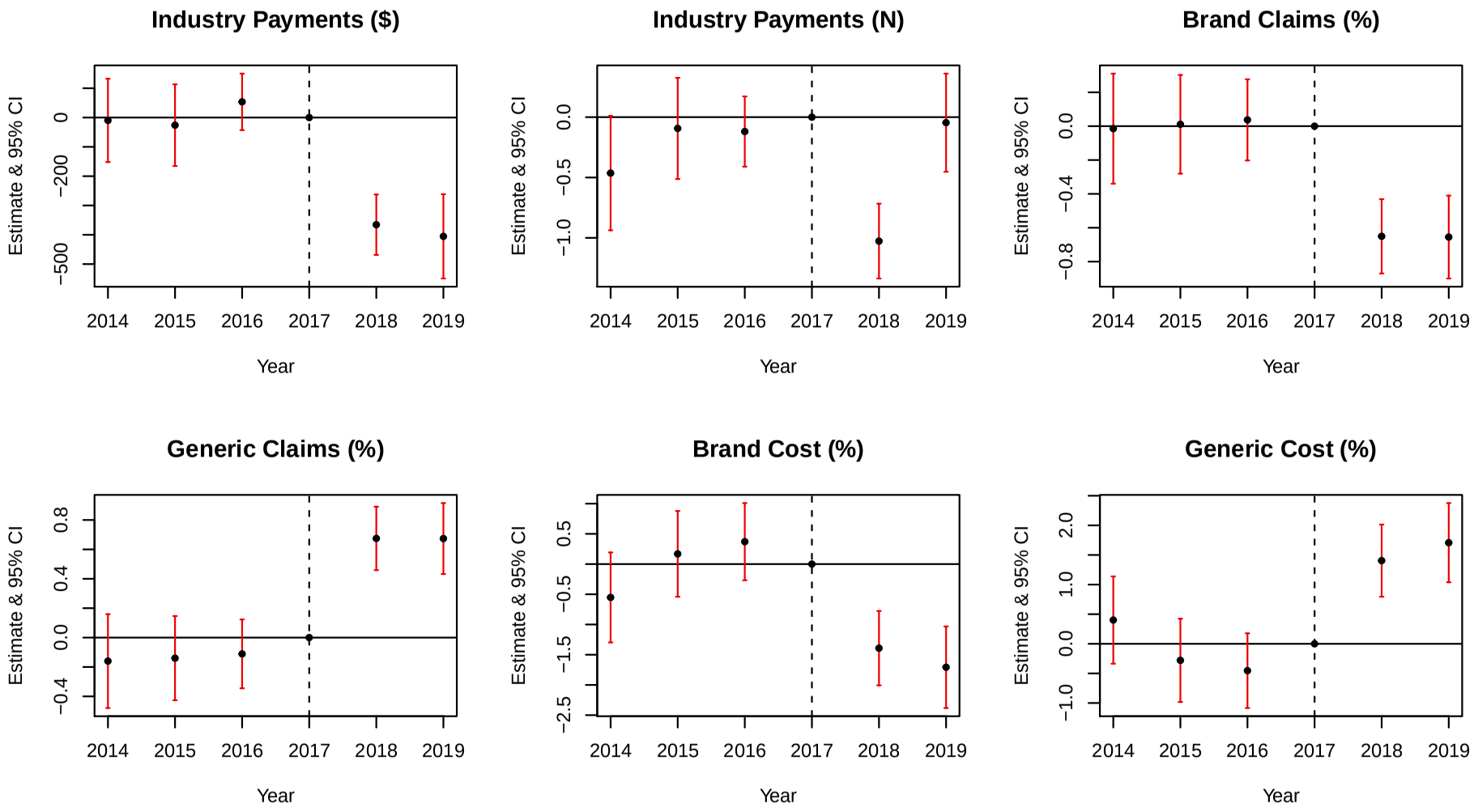


Figure 8: Heterogenous Treatment Effects by Pre-policy Payment Intensity

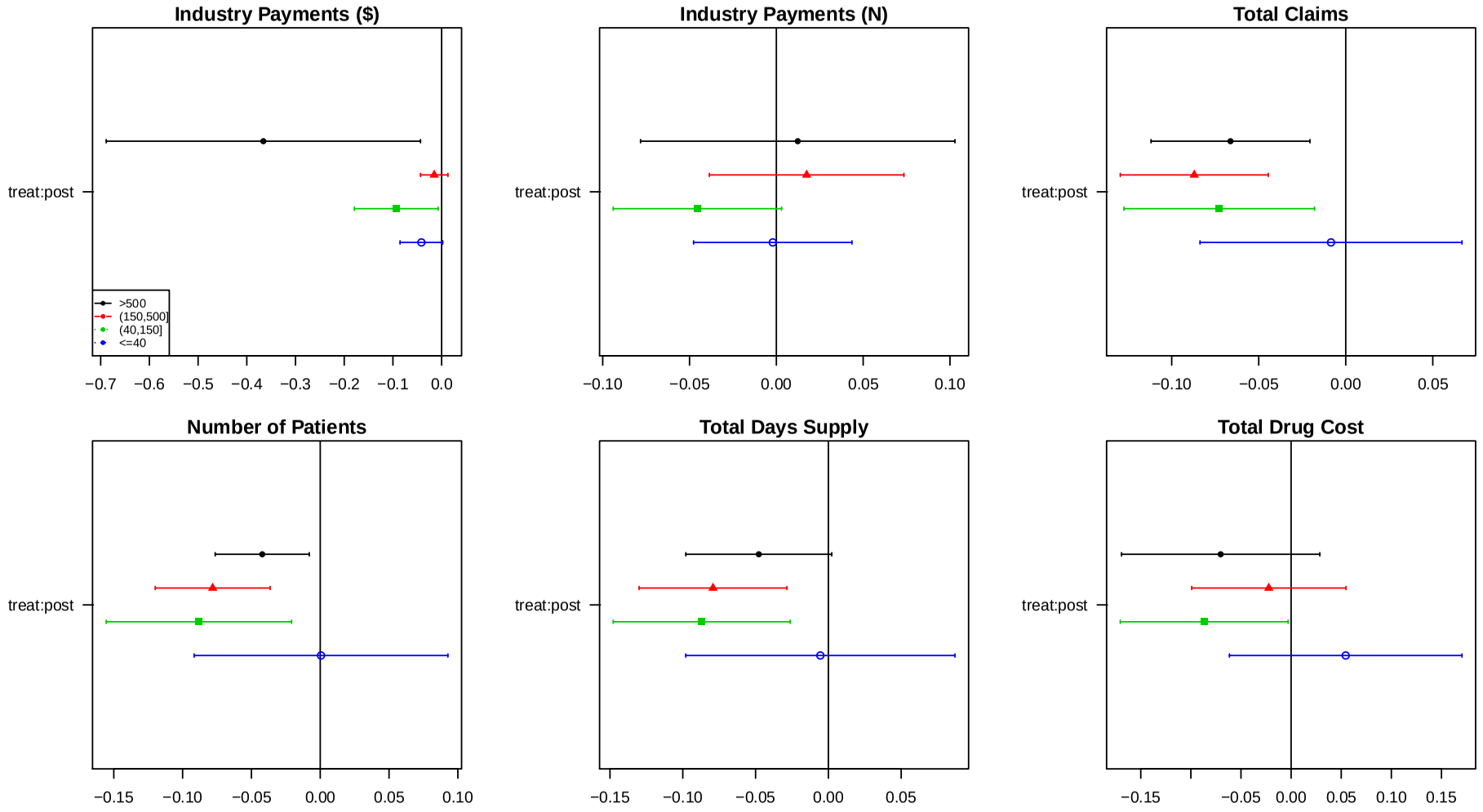


Figure 9: Heterogenous Treatment Effects by Drugs' Age

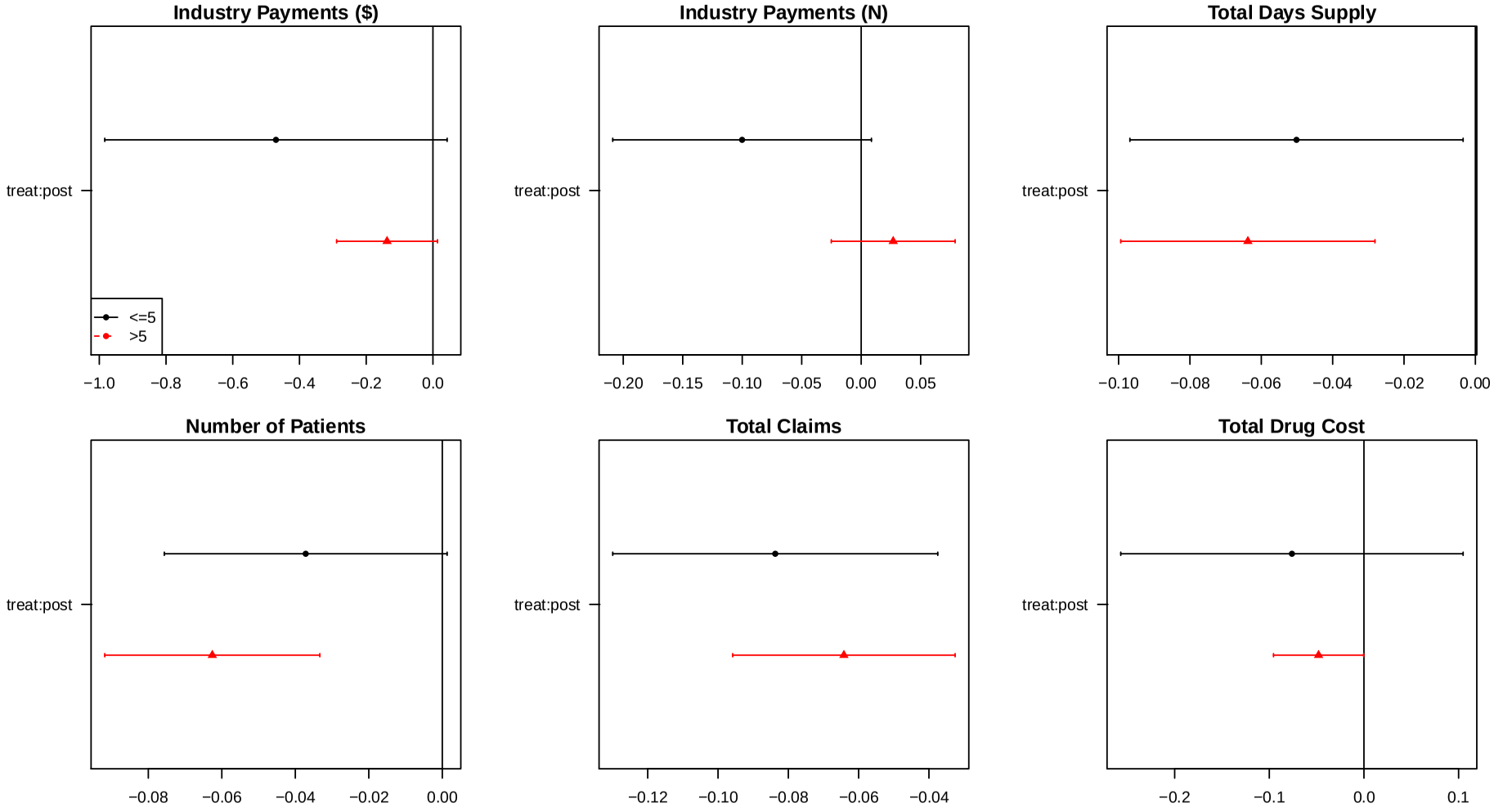


Table 1: Categories of Industry Payment Nationwide (2014-2019)

	Percent of Total			Summary Statistics ($)	
	(1)	(2)	(3)	(4)	(5)
	Value	Frequency	Physicians	Mean	Median
Compensation for Services Other Than Consulting	50.97	2.24	5.24	1,953	2,550
Food and Beverage	20.76	93.97	99.47	17.7	13.4
Consulting Fee	13.74	0.57	6.51	1,947	950
Travel and Lodging	9.9	3.03	5.87	287	153
Honoraria	3.01	0.14	1.54	1,890	1,800
Compensation for Faculty or Speaker (non-accr.)	1.63	0.07	0.59	2,083	2,000
Total	3.63 B	$42.6 M	735,462	$1,527	$119.6

Table 2: Summary Statistics for Various Outcomes (2014-2019)

Outcomes/States	NJ	NY	PA	Total
Number of Drugs	441	478	428	549
Number of Physicians	2,133	4,648	3,178	9,959
Industry Payments ($)	265.1	294.2	264.5	278
Industry Payments (N)	2.3	2.1	2.2	2.18
Total Days Supply	1,697.5	1,943.3	1,405.3	1,710.8
Number of Patients	11.6	13.2	10.3	11.9
Total Claims	40.9	52.1	39.7	45.5
Total Drug Cost	27,204.3	29,454.6	22,988.8	26,813.1

Table 3: Effect of Policy on Dollar Value and Frequency of Industry Payments

	Total	Comp.other	Food	Consulting	Travel	Comp.faculty	Honoraria
A: Industry Payments (USD)							
Treat × Post	-22.30***	-14.02***	-5.938***	-1.173	-1.515***	-0.5923*	0.3151
	(3.418)	(2.470)	(0.2083)	(0.8893)	(0.4825)	(0.3447)	(0.3905)
Pre-policy mean	83.7	46.09	18.52	8.02	7.09	1.77	2.01
B: Industry Payments ($N \times 1000$)							
Treat × Post	-28.74***	-7.022***	-15.83*	-0.6377**	-6.735***	-0.2435	0.1139
	(9.824)	(1.272)	(8.915)	(0.2843)	(1.582)	(0.1672)	(0.1880)
Pre-policy mean	1003	24	943	5	26	1	1
Observations	4,359,666	4,287,867	4,291,909	4,287,835	4,287,867	4,287,822	4,287,822
No. physicians	31,466	31,466	31,466	31,466	31,466	31,466	31,466

Physician-year and Physician-drug fixed effects are always included.
Standard errors are in parentheses and are clustered by physicians.
Significance levels: *=10%, **=5%, ***=1%.

Table 4: Effect of Policy on Industry Payments, Prescriptions Volume and Cost

	Payments ($)	Payments (N)	Total Claims	Number of Patients	Total Days Supply	Total Drug Cost ($)
	(1)	(2)	(3)	(4)	(5)	(6)
Difference-in-differences model						
Treat × Post	-63.20**	-0.0034	-3.052***	-0.6682***	-99.70***	-1,288.3*
	(25.14)	(0.0590)	(0.6230)	(0.1455)	(25.92)	(698.3)
Event study model						
Year 2019	-53.16	0.0776	-2.857***	-0.6243***	-122.2***	-1,001.7
	(35.32)	(0.0651)	(0.6248)	(0.1420)	(26.01)	(669.6)
Year 2018	-89.07***	-0.1167**	-2.197***	-0.4768***	-90.12***	-500.6
	(23.14)	(0.0533)	(0.4003)	(0.0885)	(16.09)	(456.7)
Year 2017 (omitted)	0	0	0	0	0	0
Year 2016	12.21	-0.0442	-0.0551	-0.0945	-18.40	364.8
	(16.95)	(0.0363)	(0.4094)	(0.0922)	(15.60)	(390.3)
Year 2015	-2.839	-0.0258	0.6588	0.1779	-8.109	659.0
	(22.26)	(0.0534)	(0.6437)	(0.1454)	(24.56)	(711.3)
Year 2014	-15.00	-0.2244***	0.2474	0.1484	-30.57	1,417.1
	(26.62)	(0.0701)	(0.7777)	(0.1748)	(30.24)	(952.3)
Pre-policy mean	328.11	2.67	44.49	11.92	1,687	26,088
No. physicians	9,934	9,934	9,934	9,934	9,934	9,934
Observations	528,192	528,192	528,192	528,192	528,192	528,192

Physician-year and Physician-drug fixed effects are always included.
Standard errors are in parentheses and are clustered by physicians.
Significance levels: *=10%, **=5%, ***=1%.

Table 5: Effect of Policy on Heavy Receivers

	Industry Payments ($)	Industry Payments (N)	Total Claims	Number of Patients	Total Days Supply	Total Drug Cost ($)
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	-643.7***	-0.8870**	-7.319***	-1.869***	-274.0**	-4,943.0
	(200.5)	(0.3536)	(2.817)	(0.6197)	(122.1)	(4,642.4)
Pre-policy mean	3068.48	8.44	69.17	18.34	2,947.59	71,343
No. physicians	497	497	497	497	497	497
Observations	44,850	44,850	44,850	44,850	44,850	44,850

Physician-year and Physician-drug fixed effects are always included.
Standard errors are in parentheses and are clustered by physicians.
Significance levels: *=10%, **=5%, ***=1%.

Table 6: Placebo with Doctors Never Engaged With Drug Firms

	Total Claims	Number of Patients	Total Days Supply	Total Drug Cost ($)
	(1)	(2)	(3)	(4)
Placebo Estimates	3.944	2.961	-75.11*	-841.2
	(4.884)	(3.364)	(41.00)	(993.6)
Pre-policy mean	25.91	7.91	842.44	12,355
No. Physicians	3,935	3,935	3,935	3,935
Observations	295,606	295,606	295,606	295,606
Actual Estimates	-3.052***	-0.6682***	-99.70***	-1,288.3*
	(0.6230)	(0.1455)	(25.92)	(698.3)
Pre-policy mean	44.49	11.92	1,687	26,088
No. Physicians	9,934	9,934	9,934	9,934
Observations	528,192	528,192	528,192	528,192

Physician-year and Physician-drug fixed effects are always included.
Standard errors are in parentheses and are clustered by physicians.
Significance levels: *=10%, **=5%, ***=1%.

Table 7: Effect of Policy on Industry Payments and Brand Vs. Generic Prescribing

	Industry Payments ($)	Industry Payments (N)	Brand Claims (%)	Generic Claims (%)	Brand Cost (%)	Generic Cost (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Difference-in-differences model						
Treat × Post	-389.9***	-0.3674*	-0.6612***	0.7768***	-1.546***	1.639***
	(58.14)	(0.1967)	(0.1022)	(0.1004)	(0.2514)	(0.2483)
Event study model						
Year 2019	-405.4***	-0.0457	-0.6550***	0.6736***	-1.707***	1.707***
	(73.37)	(0.2075)	(0.1249)	(0.1231)	(0.3444)	(0.3411)
Year 2018	-365.6***	-1.027***	-0.6506***	0.6746***	-1.392***	1.404***
	(52.58)	(0.1580)	(0.1119)	(0.1101)	(0.3136)	(0.3107)
Year 2017 (omitted)	0	0	0	0	0	0
Year 2016	53.60	-0.1192	0.0371	-0.1108	0.3706	-0.4537
	(49.20)	(0.1482)	(0.1223)	(0.1194)	(0.3257)	(0.3219)
Year 2015	-26.09	-0.0933	0.0110	-0.1402	0.1686	-0.2796
	(71.02)	(0.2139)	(0.1487)	(0.1462)	(0.3618)	(0.3586)
Year 2014	-9.771	-0.4637*	-0.0145	-0.1599	-0.5520	0.4013
	(72.51)	(0.2417)	(0.1659)	(0.1629)	(0.3798)	(0.3759)
Pre-policy mean	1,248.4	14.8	19.9	80.1	53	47
No. physicians	74,331	74,331	74,331	74,331	74,331	74,331
Observations	445,986	445,986	445,986	445,986	445,986	445,986

Physician and year fixed effects are always included.
Standard errors are in parentheses and are clustered by physicians.
Significance levels: *=10%, **=5%, ***=1%.

Table 8: Distribution of Dollar Value of Industry Payments Per Doctor-year (2014-2017)

	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
Average Industry Payments ($)	1-40.9	40.9-160.5	160.5-556.2	556.2-365,096
Approximate Bin Intervals	≤ 40	(40 - 150]	(150 - 500]	> 500
Number of Doctors in Each Bin	2,450	2,353	2,471	2,660

Table 9: Summary Statistics by Drug Age (2014-2017)

	≤ 5	> 5
Number of Observations	116,596	411,596
Number of Doctors	6,470	9,686
Number of Drugs	213	336
Percent of Industry Payments ($)	37%	63%
Percent of Industry Payments (N)	25%	75%