# Curbing Pharma Influence: The Effect of Marketing Restrictions on Physicians' Prescribing Behavior and Healthcare Expenditure*

Hamidreza Habibi

December 26, 2024

**Abstract**

The impact of direct-to-physician marketing and its regulation on prescribing behavior, drug expenditures, and patient outcomes remains contested. The pharmaceutical industry argues that such marketing keeps doctors informed about new medicines, while critics express concerns about potential distortions in prescribing patterns, prompting calls for stricter regulation. Some states have begun adopting such regulations, but little is known about their effects on prescribing behavior and healthcare expenditures. New Jersey implemented a policy in January 2018, imposing significant restrictions on direct-to-physician marketing, including limits on meal payments and caps on remuneration for consulting and speaking engagements. Using this policy as an exogenous source of variation and three federal administrative databases in a difference-in-difference event-study design, I estimate a 23% reduction in the dollar value of marketing received and a 4.4% decrease in the prescribing of marketed drugs by New Jersey prescribers compared to their peers in New York and Pennsylvania. I also estimate a 6% relative decline in overall drug expenditures, driven in part by a welfare-enhancing shift from branded to generic prescribing. The policy's impacts were most pronounced among prescribers who received the highest payments prior to implementation, particularly for promotional speaking, with no significant change observed among those receiving limited or no payments. The policy affected both new and established drugs, suggesting that doctor-pharma financial ties are not purely informational.

Keywords: Pharmaceutical Marketing, Prescribing Behavior, Drug Expenditure, Welfare

JEL Classification: D04, H75, I11, I18

*Click here for the latest version

# 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 to physicians and medical professionals nationwide (CMS, 2019).[1] Pharmaceutical companies spend twice as much on marketing as they do on research and development (R&D), with Direct-to-Physician Marketing (DTPM) comprising about 85% of this expenditure (Gagnon and Lexchin, 2008; National Academies of Sciences et al., 2017; Lexchin, 2018; Trusts, 2015). Furthermore, 93% of physicians nationwide reported having some type of financial relationship with the pharmaceutical industry (Campbell et al., 2007). Given the significant investment by pharmaceutical companies in these initiatives, the widespread physician involvement, and the potential negative impacts of industry payments on prescribing behavior and patient welfare, there have been growing calls for stricter regulation of DTPM. However, there is limited understanding of the effectiveness of these regulations in reducing industry payments and changing prescribing patterns, healthcare expenditures, and patient health outcomes.

Proponents of the practice argue that these marketing interactions aim to educate doctors about new drugs. According to a pharmaceutical industry trade group, these encounters are crucial for ensuring that healthcare professionals have 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 appropriate entities to educate doctors about new drugs. As Marcia Angell, a prominent critic, expressed in an interview,[2] "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, both state and federal authorities have raised concerns about the potential negative effects of physician-pharma financial relationships on prescribing behavior, healthcare expenditures, and patient outcomes, leading to the implementation of measures aimed at addressing these issues. Beginning in the early 2000s, several states responded by introducing varying levels of disclosure and restrictions on Direct-to-Physician Marketing (DTPM).[3]

[1] These figures account only for general payments. Additionally, firms paid $6 billion for research-related payments and $1.42 billion for ownership and investment interests.

[2] Marcia Angell is a faculty member at Harvard Medical School, the first woman to serve as editor-in-chief of the New England Journal of Medicine, and the author of The Truth About the Drug Companies: How They Deceive Us and What to Do About It.

[3] States with regulations include MA, VT, WV, DC, CA, and NV. Further details are provided in

At the federal level, to enhance transparency in physician-industry relationships, the Physician Payments Sunshine Act (PPSA) was enacted in 2010, requiring drug and medical device companies to track and publicly report payments to physicians.[4] Recently, in a rare and significant fraud alert issued in November 2020, the Department of Health and Human Services Office of Inspector General (OIG) highlighted numerous fraud cases related to industry-sponsored speaker programs, which violated federal statutes.[5,6]

However, despite these regulatory efforts, the literature remains inconclusive on whether regulating payments is beneficial. 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 on the nature of the payments involved. 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.[7]

In this study, I provide new insights into the effects of regulations that restrict direct-to-physician marketing (DTPM) on prescribing behavior, prescription drug spending, and patient health outcomes. The analysis links the comprehensive Open Payments dataset, which tracks monetary and in-kind transfers from pharmaceutical companies to physicians, with prescription data for Medicare Part D enrollees from 2014 and 2019.[8] I focus on a unique New Jersey (NJ) policy implemented in 2018, which imposed restrictions on several channels of interaction between physicians and pharmaceutical companies. I assess its impact on DTPM and the resulting changes in physicians' prescribing behavior.[9]

---

Section 2.2.

[4]The PPSA is a disclosure policy only; it does not ban or restrict financial relationships between industry and physicians.

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

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

[7]Spurling et al. (2010) provides a comprehensive review of medical literature on the impact of marketing activities on the quality, quantity, and cost of prescribed drugs. The authors conclude that the main obstacle to obtaining a clear answer lies in the limitations of the existing research.

[8]I use 2019 as the final year of analysis to avoid disruptions to payments caused by the COVID-19 pandemic.

[9]According to Sullivan (2018), New Jersey is the first state to cap physician income from pharmaceutical interactions and regulate physician conduct, rather than targeting pharmaceutical companies. While other states have imposed various restrictions on practitioner-industry relationships, none have imposed income caps.

Prior to the policy, physicians in New Jersey (NJ) and neighboring states, New York (NY) and Pennsylvania (PA), exhibited similar trends in the frequency and value of payments from pharmaceutical firms, prescription volumes, and overall spending on the drugs they prescribed.[10] Following the policy's enactment in January 2018, trends diverged significantly between NJ physicians and those in control states unaffected by the regulations. The results from the event study difference-in-differences model reveal that NJ prescribers received $17.78 less per drug annually, representing a 23% reduction from the pre-policy mean of $76.74. This decline was largely driven by substantial reductions in food-related payments (30%), compensation outside of consulting (26%), and travel-related remunerations (19%).[11] The overall reduction in payment frequency was modest at 1.8%, primarily due to the prevalence of food payments, which were not limited by the policy.[12] However, notable declines were observed in other categories: a 23% reduction in compensation outside consulting, 23% in travel payments, and 14% in consulting fees.

The reduced-form results confirm that NJ doctors decreased prescription volumes of marketed drugs in both extensive (4.7% for total claims, 3.45% for the number of patients) and intensive margins (5% for total days supply) post-policy. Additionally, I estimate a relative decline of 6% in prescription drug spending. Further investigation into the sources of this spending decline, using prescriber-level data, reveals that the policy encouraged a shift from branded, more expensive drugs—commonly targeted by pharmaceutical firms—toward lower-cost generic alternatives. Specifically, there was a 4.6% relative reduction in the volume of branded prescriptions and a 3.3% decrease in branded drug spending. A back-of-the-envelope calculation suggests that this shift saved the state of New Jersey $25 million annually during the post-policy period, compared to New York and Pennsylvania. Given that the Food and Drug Administration (FDA) only approves generic alternatives that demonstrate equivalent efficacy to branded drugs, this transition can be considered welfare-enhancing, generating significant cost savings without compromising therapeutic outcomes.[13]

[10]The selection of neighboring states as controls mitigates concerns about fundamental differences between treated and control physicians, as the physicians in these states share similar patient population and socioeconomic characteristics. Various robustness checks, including a synthetic control approach, were conducted to ensure the results are not driven by the choice of control states. Details on robustness tests are provided in the appendix (A3 and A4)

[11]Compensation outside the consulting category primarily includes payments to speakers at promotional events. A detailed definition of each category is provided in the appendix (figure 6).

[12]The NJ policy restricts the dollar value of meals but not their frequency. See Section 2.1 for more information.

[13]According to Medicare's definition, drug spending reflects amounts paid by the Part D plan, Medicare beneficiaries, government subsidies, and any other third-party payers. Therefore, it approximates the list prices announced for all drugs.

I conduct additional analyses to explore the mechanisms driving the observed results. First, given the diversity of payment types—ranging from small but frequent payments (e.g., meals) to larger, more concentrated payments (e.g., consulting and speaking fees) directed at a select group of physicians—a key question arises: Are certain physicians targeted more than others? Of particular interest are those who received the highest payments from pharmaceutical companies during the pre-policy period. These physicians are often targeted due to their high prescribing volume (direct effect) and their influence as Key Opinion Leaders (KOLs) among peers (indirect effect). To examine this group, I focus on the top 5% of physicians in NJ, NY, and PA who received the highest payments from the pharmaceutical industry. A median doctor in this group received $21,371 annually during the pre-policy period—a disproportionately higher amount compared to physicians in the remaining 95% of the distribution. They also issued more prescriptions and incurred higher expenditures than their counterparts in the remaining 95%. This group experienced an average annual reduction of $391.5 in industry payments per drug, a 17% decrease from the pre-policy mean of $2,369. Additionally, they saw a 7% decrease in payment frequency, primarily driven by fewer speaker program engagements. The policy's impact on prescribing behavior was more pronounced in this group, with an 8% reduction in total prescription volume—nearly double the decline observed among median-prescribing doctors. These findings suggest a causal relationship between payments and prescribing behavior at the physician level.

Second, to further explore the welfare implications of these regulations for consumers, I test the plausibility of the industry's claim that these payments primarily provide important information to doctors, which ultimately benefits consumers. If this were the case, we would expect reductions in prescription volumes to be only concentrated among newer, lesser-known drugs, leaving prescriptions for older drugs unaffected. However, estimates based on the FDA approval dates of drugs reveal that the policy impacts both newer and older drugs, suggesting that the financial relationships between physicians and pharmaceutical firms are not purely informational.

This study contributes fresh insights to the literature in several ways. First, few studies have examined the effects of disclosure and restrictive policies at the federal, state, and medical school levels on prescribing behavior (Larkin et al., 2017; Li et al., 2022; Guo et al., 2020; King and Bearman, 2017; Grennan et al., 2018). For example, using an event-study design, Li et al. (2022) found that the Physician Payments Sunshine Act (PPSA) significantly reduced branded drug prescriptions without affecting generics, suggesting the law successfully curbed drug spending by limiting branded prescriptions, at least in the short term. Similarly, King

and Bearman (2017) show that state policies banning or restricting gifts from pharmaceutical representatives are likely more effective than disclosure policies alone. Guo et al. (2020) report reductions in prescriptions across all drug classes, including generics. Larkin et al. (2017) investigated restrictive measures in medical centers, finding a modest but significant reduction in the prescribing of promoted drugs after policy implementation. Finally, Grennan et al. (2018) used a small sample of drugs and variations in hospital policies banning pharmaceutical representatives to demonstrate that even a meal can increase the prescription of a promoted statin by around 70%.

Most of these state-level policies were enacted before the PPSA, relying on more limited data, as they could not fully benefit from the rich financial information now available through the PPSA. This paper adds to the literature by using the detailed financial transfer data published post-PPSA and employing valid counterfactuals to assess the impact of New Jersey's policy—the only state to hold physicians directly accountable for violations rather than pharmaceutical companies. With data reported by firms to Open Payments and responsibility placed on physicians, the New Jersey policy minimizes the risk of false reporting, unlike the self-reported data often used in pre-PPSA analyses. Additionally, this paper examines the effects of the policy across different channels of pharmaceutical promotion, identifying which ones are most effective in influencing prescribing behavior. It also includes heterogeneity analyses to explore the types of prescribers and drugs most susceptible to these marketing activities. Unlike studies that focus on a single drug or drug class, this paper examines all Part D drugs, making the findings broadly applicable.[14] Furthermore, this study investigates how restrictive policies can facilitate a shift from branded to generic prescribing, yielding significant cost savings for both patients and payers.

Second, a large body of work, particularly in medical journals, has consistently found a positive association between 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). For example, Mitchell et al. (2021) reviewed 101 studies and found that 89 of them reported a positive association between pharmaceutical marketing, greater prescribing of promoted drugs, higher drug costs, and a preference for branded medications. However, many

[14] Shapiro (2018) stressed the importance of analyzing the full set of drugs since most policies do not target a specific drug or class.

of these studies fail to account for selection bias—namely, that pharmaceutical companies tend to focus on high-prescribing doctors—limiting their ability to establish causality. This paper contributes to the literature by applying a causal inference approach to better determine the true impact of pharmaceutical marketing on prescribing behavior and healthcare expenditure.

Third, recent studies in economics have begun using the rich data to explore the causal effects of the timing of marketing payments on prescribing behavior (Carey et al., 2021; Agha and Zeltzer, 2022; Shapiro, 2018). For example, Carey et al. (2021) use an event-study design to show that the number of patients treated and expenditures on marketed drugs increase significantly after physicians receive payments, with expenditures rising by 7.6%. Similarly, Agha and Zeltzer (2022) analyze large compensation payments made to key opinion leaders and find both direct and spillover effects on prescribing. Their study shows that payments lead to a notable increase in prescriptions for the marketed drug, not only by the paid physician but also by their peers. Over a three-year period, prescriptions for marketed anticoagulants increased by 23%, with peer spillovers accounting for a quarter of that growth. Additionally, DeJong et al. (2016b) find that even modest payments, such as meals under $20, make physicians more likely to prescribe brand-name drugs when generic alternatives are available. This paper contributes to this emerging body of work by examining the impact of a statewide regulation on a broad range of firm-physician interactions, from small payments for meals to substantial fees for speaking and consulting, and how regulating these interactions influences prescribing patterns.

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 welfare 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.[15] For the purpose of this study, it is essential to cat-

[15]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.

egorize 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).[16,17]

The second category under consideration is Compensation for Services, which typically 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. 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, exploring various categories of payments.

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

[17]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

## 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.[18] California and Nevada required pharmaceutical firms to comply with the Pharmaceutical Research and Manufacturers of America (PhRMA) code of conduct.[19] 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.[20] 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.[21] 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."*

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

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

[20] 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.

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

The general prohibitions in the regulations include the following:

1. Meals with a market value larger than $15.[22]
2. Any financial benefit or benefit in kind.
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.[23]

The rule applies to physicians with an active NJ license who either practice in NJ or have NJ patients.[24] Educational events, medical devices, contracts made before Jan 15, 2018, and firms' employees are exempted.[25] 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. Since companies are required to report to Open Payments, holding physicians accountable is purposefully designed to minimize the risk of inaccurate reporting.

# 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.[26] I observe detailed information about the type, dollar value, and frequency of payments, doctors' and firms' IDs, drugs' names,

[22] 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.

[23] 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.

[24] 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.

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

[26] 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.

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.[27] The focus of this study is on general payments, which have 16 different categories from which only six categories should be affected by policy and are included in the analyses.[28] 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.[29] 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.[30,31] 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

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

[28] 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.

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

[30] 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.

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

status.[32] Additionally, I cannot differentiate 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.[33]

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 1,225,369 observations associated with 18,191 physicians and 652 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 year t, I estimate the event-study specification:

$$Y_{pdt} = NJ_p \times \sum_{\substack{t=2014 \\ t\neq 2017}}^{2019} \beta_t I(t) + \alpha_{pd} + \gamma_{td} + \epsilon_{pdt} \tag{1}$$

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. $NJ_p$ is an indicator variable, taking a value of 1 if the doctors are licensed in NJ and 0 otherwise. $I(t)$ represents the event time indicator, with the year prior to the policy (2017) as the omitted reference time. Therefore,

[32] 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 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.

[33] 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.

each estimate of $\beta_t$ measures the changes in outcomes in NJ compared to neighbouring states during year t, as measured from the year prior to the policy. The fixed effect $\alpha_{pd}$ allows a different intercept for each physician-drug combinations. $\gamma_{td}$ 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 the 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.[34]

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.[35] 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, 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 of the matching process is provided in the Appendix.

[34]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.

[35]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.

# 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 33,334 unique physicians and total of 5,298,102 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.[36]

Figure 1 presents the monthly averages of industry payments received by prescribers in New Jersey, the neighboring states of New York and Pennsylvania, and other U.S. states. The policy had an immediate effect on the dollar value of industry payments to New Jersey prescribers, with no evidence of spillover effects in neighboring states.[37] 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 Figure 2 and Figure 3 and the first column of Table 3. Figure 2 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 $18 less per drug per year post-policy, representing a 23% reduction from the pre-policy mean of $76.7. This reduction in dollar value is consistent and remains relatively stable throughout the post-policy periods. Figure 3 illustrates the effect of the policy on the frequency of industry payments. The total reduction in frequency of industry payments is small, at about 1.8% of the sample mean [38]. 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 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.

[36] 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.

[37] The monthly time series indicates no spillover effects to neighboring states. The increase observed in neighboring states appears to be part of a national trend, as similar patterns are present in other states. The figure also shows no anticipation effect in New Jersey, with the policy impact occurring immediately upon enactment.

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

Figure 4 and Figure 5 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 \$10.83 (a 26% decrease from the pre-policy mean) for "compensation other," \$5.3 for food (30%), and \$1.2 for travel (18.7%). 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" (23%), consulting (14%), 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 prescribing behavior. Numerous studies in the literature have found that industry payments increase the prescribing rates and expenditures of the marketed drugs.[39] 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

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

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 1,225,369 observations and 18,191 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. [40]

Figure 6 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 20% from the pre-policy mean of $223.92. As 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.[41]

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 1.8 fewer claims for each drug annually to Medicare (4.7% over the pre-policy mean of 38.83). The unique number of patients for each drug also experienced a reduction of 0.3782 (3.4% over the

[40] 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.

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

pre-policy mean of 10.97). The total days' supply for each drug also reduced by 71.25 (5% over the pre-policy mean of 1,430). Furthermore, the reduction in expenditure of marketed drugs shows a relative decline of $1,193 (6% over the pre-policy mean of 20,068).

Overall, the policy substantially reduced the prescription volume and expenditure 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 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 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:

$$Y_{pt} = NJ_p \times \sum_{\substack{t=2014 \\ t \neq 2017}}^{2019} \beta_t \cdot I(t) + \alpha_p + \gamma_t + \epsilon_{pt} \tag{2}$$

The primary outcomes, $Y_{pt}$, are proportions of brand and generic claims and costs by each doctor. $\alpha_p$ and $\gamma_t$ are doctor and time fixed effects.[42]

As evidenced in Figure 8, 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 5. The results indicate a 0.97 percentage point (p.p.) reduction in the volume of brand claims submitted to Medicare by NJ doctors and a 1.114 p.p. increase in generic claims following the policy implementation. Correspondingly, there is a reduction of about 1.765 p.p. in the proportion of brand-name drug costs and an increase of 2.030 p.p. in generic drug costs.

Pre-policy averages show that while brand-name prescriptions constituted approximately 20% of total claims, the costs associated with them accounted for 53% of overall expenditures, highlighting the significant cost-saving potential of shifting to generic prescribing. The regulations in New Jersey resulted in a 1.55 percentage point decrease in annual brand-name drug expenditures per doctor, accompanied by a corresponding 1.64 percentage point increase in expenditures on generic drugs. Assuming the findings of this study are generalizable, given the pre-policy average annual costs of \$160,428 for brand-name drugs and \$45,137 for generic drugs per doctor in New Jersey, a straightforward calculation indicates a \$1,915 reduction ((.0203 $\times$ \$45,137) – (.01765 $\times$ \$160,428)) in total expenditure per doctor-year in New Jersey compared to their counterparts in New York and Pennsylvania. With 13,238 NJ prescribers in the sample, this translates to approximately \$25 million in annual savings post-policy in NJ compared to NY and PA.

[42]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.

# 6 Mechanisms

## 6.1 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; 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 910 physicians (the top 5%) who received the largest payments from the pharmaceutical industry between 2014 and 2017 in NJ, NY, and PA. The top five medical specialties targeted by pharma promotions were Cardiologists (17%), Endocrinologists (13%), Neurologists (12%), Internal Medicine physicians (10%), and Psychiatrists (6%). Table 6 shows that a median doctor in this group received an average of $21,371 annually from the pharmaceutical industry—156 times more than a median doctor in the remaining 95%. They also received the highest number of payments and issued significantly more prescriptions for a greater number of distinct drugs. Furthermore, they had a larger number of patients and incurred almost four times higher expenditure compared to a median doctor in the remaining 95%, consistent with findings in the literature that pharmaceutical promotions disproportionately target high-volume prescribers, who are often key opinion leaders (KOLs) (Fugh-Berman and Ahari, 2007; Fugh-Berman, 2008; Carey et al., 2021).

The DiD estimates reported in Table 7 show that these doctors received, on average, $391.5 less per drug after the policy—almost 9 times the reduction seen for other doctors. This represents a 17% 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 7% 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 8% 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.

## 6.2 Heterogeneity by Payment Intensity

The Average Treatment on the Treated Effects (ATT) presented in sections 5.1 and 5.2 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 9 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. [43]

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 5.7. 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. [44]

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

[44] 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

## 6.3 Heterogeneity by Age of the Drugs

The second important dimension of heterogeneity is based on the age of drugs at the time of the policy implementation.[45] 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.[46]

The median age of the drugs in the sample is 8 years, with a mean of 9.5 years. Table 9 presents summary statistics for drugs based on the FDA exclusivity cutoff during the pre-policy years. Out of 1,225,369 observations, only 303,174 (approximately 25%) are for drugs less than 5 years old. In total, just 37% of industry payments by dollar value and 29% by frequency are for drugs still within the exclusivity period, with the vast majority of payments directed toward older drugs. This suggests that information transmission may not be the only objective of pharmaceutical promotions. In addition to summary statistics, Figure 10 reports the policy's effect on different drugs based on the 5-year FDA exclusivity cutoff. The results show an average 20% reduction in industry payments and about a 5% reduction in prescription volumes and expenditures for established drugs, indicating that the overall reduction is not solely driven by the newest drugs. This finding challenges the pharmaceutical companies' claims about the purely informational nature of DTPM. Furthermore, some older drugs with generic alternatives may be the driving force behind the transition observed in Section 5.3." [47]

attributable to heavy receivers.

[45] 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.

[46] 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.

[47] 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.

### 6.4 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. [48]

Table 10 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).

## 7 Discussions and Welfare 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

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

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 introduce 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.[49]

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 Ser-

[49]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

vices, 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.

The welfare implications of the policy can be viewed from two perspectives: cost savings for both patients and the healthcare system, and patient health outcomes. The reduced-form analysis and brand-to-generic transition suggest that the policy generated substantial annual savings in New Jersey compared to neighboring states. According to the FDA, generic drugs offer the same efficacy as their branded counterparts. Therefore, the shift from branded to generic drugs enhances welfare by reducing healthcare costs without compromising patient outcomes.

However, one limitation of this study is its inability to determine whether the policy inadvertently led to a reduction in prescribing certain drugs without a corresponding shift to generics—particularly in cases where no generics are available. If such instances occurred, the policy could have negatively impacted patient welfare by limiting access to appropriate medications. Nevertheless, given that approximately 70% of pharmaceutical promotions target older drugs for non-life-threatening conditions, this concern may be less significant. Overall, consistent with the literature, the results of this study suggest that well-designed policies that effectively curb problematic aspects of financial interactions in pharmaceutical promotions are welfare-enhancing.[50].

# 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 prior to implementation 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 established drugs, supporting the hypothesis that pharmaceutical promotions are not purely informational.

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

# References


AAM (2019). The case for competition 2019 generic drug biosimilars access savings in the u.s. report. https://accessiblemeds.org/sites/default/files/2019-09/AAM-2019-Generic-Biosimilars-Access-and-Savings-US-Report-WEB.pdf.

Adair, R. F. and Holmgren, L. R. (2005). Do drug samples influence resident prescribing behavior? a randomized trial. *The American journal of medicine*, 118(8):881–884.

Adashi, E. Y. and Cohen, I. G. (2021). Industry-Sponsored Speaker Programs—End of the Line? *JAMA*, 325(18):1835–1836.

Agha, L. and Zeltzer, D. (2022). Drug diffusion through peer networks: The influence of industry payments. *American Economic Journal: Economic Policy*, 14(2):1–33.

Anderson, B. L., Silverman, G. K., Loewenstein, G. F., Zinberg, S., and Schulkin, J. (2009). Factors associated with physicians' reliance on pharmaceutical sales representatives. *Academic Medicine*, 84(8):994–1002.

Annapureddy, A. R., Henien, S., Wang, Y., Minges, K. E., Ross, J. S., Spatz, E. S., Desai, N. R., Peterson, P. N., Masoudi, F. A., and Curtis, J. P. (2020). Association between industry payments to physicians and device selection in icd implantation. *Jama*, 324(17):1755–1764.

Brax, H., Fadlallah, R., Al-Khaled, L., Kahale, L. A., Nas, H., El-Jardali, F., and Akl, E. A. (2017). Association between physicians' interaction with pharmaceutical companies and their clinical practices: a systematic review and meta-analysis. *PloS one*, 12(4):e0175493.

Campbell, E. G., Gruen, R. L., Mountford, J., Miller, L. G., Cleary, P. D., and Blumenthal, D. (2007). A national survey of physician–industry relationships. *New England Journal of Medicine*, 356(17):1742–1750.

Carey, C., Lieber, E. M., and Miller, S. (2021). Drug firms' payments and physicians' prescribing behavior in medicare part d. *Journal of Public Economics*, 197:104402.

CMS (2019). Open payment facts. https://openpaymentsdata.cms.gov/summary.

Dana, J. and Loewenstein, G. (2003). A social science perspective on gifts to physicians from industry. *Jama*, 290(2):252–255.

Datta, A. and Dave, D. (2017). Effects of physician-directed pharmaceutical promotion on prescription behaviors: longitudinal evidence. *Health economics*, 26(4):450–468.

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

DeJong, C., Aguilar, T., Tseng, C.-W., Lin, G. A., Boscardin, W. J., and Dudley, R. A. (2016b). Pharmaceutical Industry–Sponsored Meals and Physician Prescribing Patterns for Medicare Beneficiaries. *JAMA Internal Medicine*, 176(8):1114–1122.

Dolovich, L., Levine, M., Tarajos, R., and Duku, E. (1999). Promoting optimal antibiotic therapy for otitis media using commercially sponsored evidence-based detailing: A prospective controlled trial. *Drug Information Journal*, 33(4):1067–1077.

Engelberg, J., Parsons, C. A., and Tefft, N. (2014). *Financial conflicts of interest in medicine*, volume 2297094. SSRN.

FDA (2023). Generic drugs: Questions answers. https://www.fda.gov/drugs/frequently-asked-questions-popular-topics/generic-drugs-questions-answers.

Fleischman, W., Agrawal, S., King, M., Venkatesh, A. K., Krumholz, H. M., McKee, D., Brown, D., and Ross, J. S. (2016). Association between payments from manufacturers of pharmaceuticals to physicians and regional prescribing: cross sectional ecological study. *bmj*, 354.

Freemantle, N., Johnson, R., Dennis, J., Kennedy, A., and Marchment, M. (2000). Sleeping with the enemy? a randomized controlled trial of a collaborative health authority/industry intervention to influence prescribing practice. *British journal of clinical pharmacology*, 49(2):174–179.

Frontline, P. (2002). Interview: Marcia angell.

Fugh-Berman, A. (2008). Prescription tracking and public health. *Journal of general internal medicine*, 23:1277–1280.

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

Gagnon, M.-A. and Lexchin, J. (2008). The cost of pushing pills: a new estimate of pharmaceutical promotion expenditures in the united states. *Plos medicine*, 5(1):e1.

Grennan, M., Myers, K., Swanson, A., and Chatterji, A. (2018). Physician-industry interactions: Persuasion and welfare. *NBER Working Paper*, (w24864).

Grundy, Q., Bero, L., and Malone, R. (2013). Interactions between non-physician clinicians and industry: a systematic review. *PLoS medicine*, 10(11):e1001561.

Guo, T., Sriram, S., and Manchanda, P. (2020). "let the sunshine in": The impact of industry payment disclosure on physician prescription behavior. *Marketing Science*, 39(3):516–539.

Hansen, B. B. (2004). Full matching in an observational study of coaching for the sat. *Journal of the American Statistical Association*, 99(467):609–618.

Hansen, B. B. and Klopfer, S. O. (2006). Optimal full matching and related designs via network flows. *Journal of computational and Graphical Statistics*, 15(3):609–627.

King, M. and Bearman, P. S. (2017). Gifts and influence: Conflict of interest policies and prescribing of psychotropic medications in the united states. *Social Science & Medicine*, 172:153–162.

Larkin, I., Ang, D., Steinhart, J., Chao, M., Patterson, M., Sah, S., Wu, T., Schoenbaum, M., Hutchins, D., Brennan, T., et al. (2017). Association between academic medical center pharmaceutical detailing policies and physician prescribing. *Jama*, 317(17):1785–1795.

Lexchin, J. (2018). Pharmaceutical company spending on research and development and promotion in canada, 2013-2016: a cohort analysis. *Journal of pharmaceutical policy and practice*, 11:1–6.

Li, J., Wu, B., Flory, J., and Jung, J. (2022). Impact of the affordable care act's physician payments sunshine act on branded statin prescribing. *Health Services Research*, 57(5):1145–1153.

McKinney, W. P., Schiedermayer, D. L., Lurie, N., Simpson, D. E., Goodman, J. L., and Rich, E. C. (1990). Attitudes of internal medicine faculty and residents toward professional interaction with pharmaceutical sales representatives. *Jama*, 264(13):1693–1697.

Mitchell, A. P., Trivedi, N. U., Gennarelli, R. L., Chimonas, S., Tabatabai, S. M., Goldberg, J., Diaz Jr, L. A., and Korenstein, D. (2021). Are financial payments from the pharmaceutical industry associated with physician prescribing? a systematic review. *Annals of internal medicine*, 174(3):353–361.

National Academies of Sciences, E., Medicine, et al. (2017). *Making medicines affordable: a national imperative*.

Office of Inspector General, D. o. H. and Human Services, Washington, D. . (2020). Special fraud alert: Speaker programs. https://oig.hhs.gov/documents/special-fraud-alerts/865/SpecialFraudAlertSpeakerPrograms.pdf.

Orlowski, J. P. and Wateska, L. (1992). The effects of pharmaceutical firm enticements on physician prescribing patterns: there's no such thing as a free lunch. *Chest*, 102(1):270–273.

Ornstein, C., Tigas, M., and Jones, R. G. (2016). Now there's proof: docs who get company cash tend to prescribe more brand-name meds. *Dollars for Doctors. New York, NY: ProPublica*.

Park, A. (2024). Generics face "knowledge gap" against brand loyalty: Globaldata. https://www.fiercepharma.com/marketing/generic-drug-makers-must-close-knowledge-gap-overcome-doctors-brand-loyalty-globaldata.

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

Pharmedout (2023). Drug reps. https://georgetown.app.box.com/s/ativoq6izpx2bnqf08s7qodv0sd1pu2z.

PhRMA (2020). The pharmaceutical research and manufacturers of america (phrma): Code on interactions with health care professionals. https://phrma.org/stem/code-on-interactions-with-health-care-professionals.

Shapiro, B. T. (2018). Informational shocks, off-label prescribing, and the effects of physician detailing. *Management Science*, 64(12):5925–5945.

Spurling, G. K., Mansfield, P. R., Montgomery, B. D., Lexchin, J., Doust, J., Othman, N., and Vitry, A. I. (2010). Information from pharmaceutical companies and the quality, quantity, and cost of physicians' prescribing: a systematic review. *PLoS medicine*, 7(10):e1000352.

Steinman, M. A., Shlipak, M. G., and McPhee, S. J. (2001). Of principles and pens: attitudes and practices of medicine housestaff toward pharmaceutical industry promotions. *The American journal of medicine*, 110(7):551–557.

Stuart, E. A., King, G., Imai, K., and Ho, D. (2011). Matchit: nonparametric preprocessing for parametric causal inference. *Journal of statistical software*.

Sullivan, T. (2018). New jersey governor christie introduces regulation to cap physician-pharma relationships. https://www.policymed.com/2017/09/christie-introduces-regulation-to-cap-physician-pharma-relationships.html.

Trusts, P. C. (2015). Persuading the prescribers: pharmaceutical industry marketing and its influence on physicians and patients.

Wood, S. F., Podrasky, J., McMonagle, M. A., Raveendran, J., Bysshe, T., Hogenmiller, A., and Fugh-Berman, A. (2017). Influence of pharmaceutical marketing on medicare prescriptions in the district of columbia. *PloS one*, 12(10):e0186060.

Yeh, J. S., Franklin, J. M., Avorn, J., Landon, J., and Kesselheim, A. S. (2016). Association of industry payments to physicians with the prescribing of brand-name statins in massachusetts. *JAMA internal medicine*, 176(6):763–768.

Young, A., Chaudhry, H. J., Pei, X., Arnhart, K., Dugan, M., and Steingard, S. A. (2019). Fsmb census of licensed physicians in the united states, 2018. *Journal of Medical Regulation*, 105(2):7–23.

Figure 1: Monthly Average of Industry Payments: NJ vs. Other States

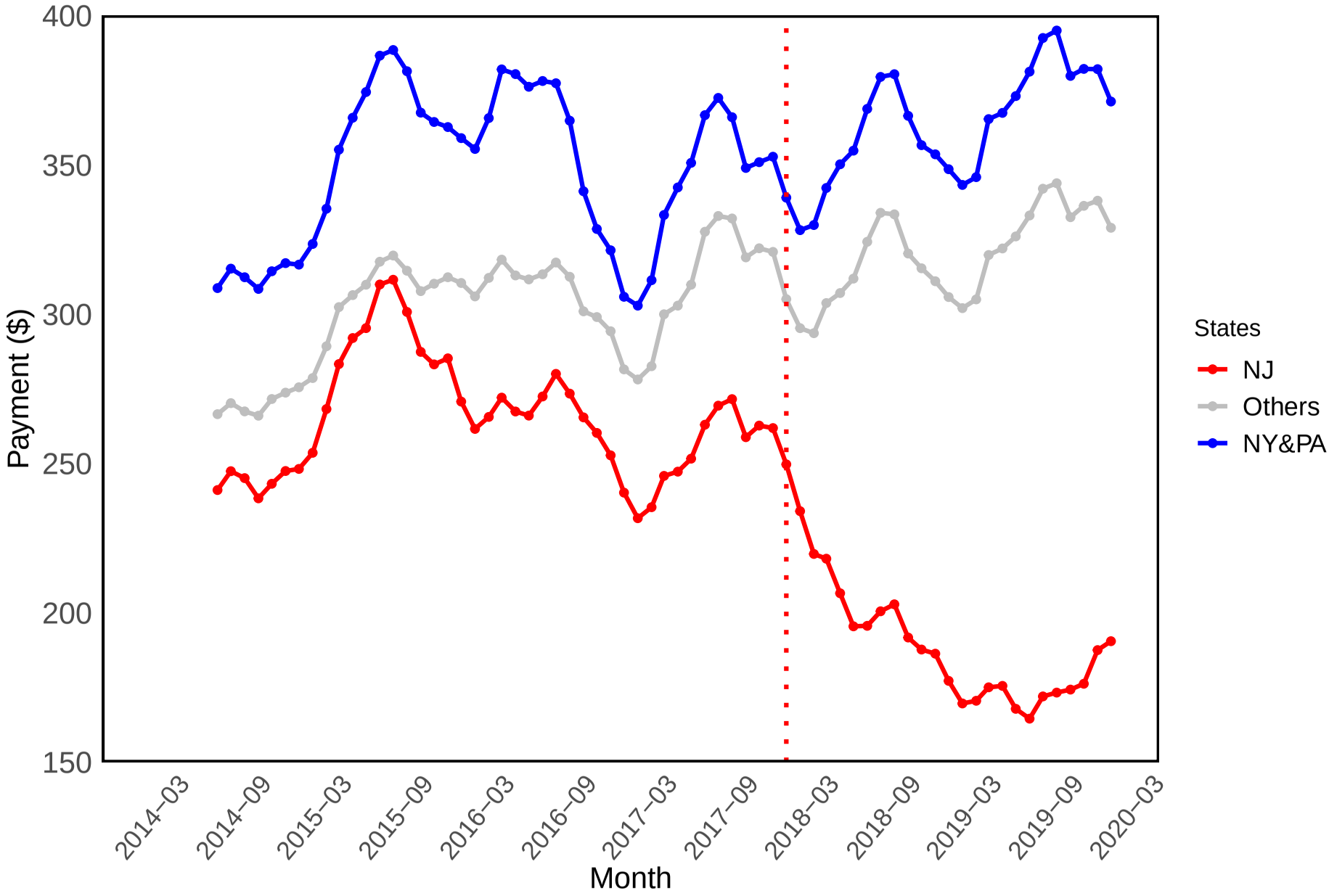


Figure 2: Effect of Policy on Dollar Value of Industry Payments

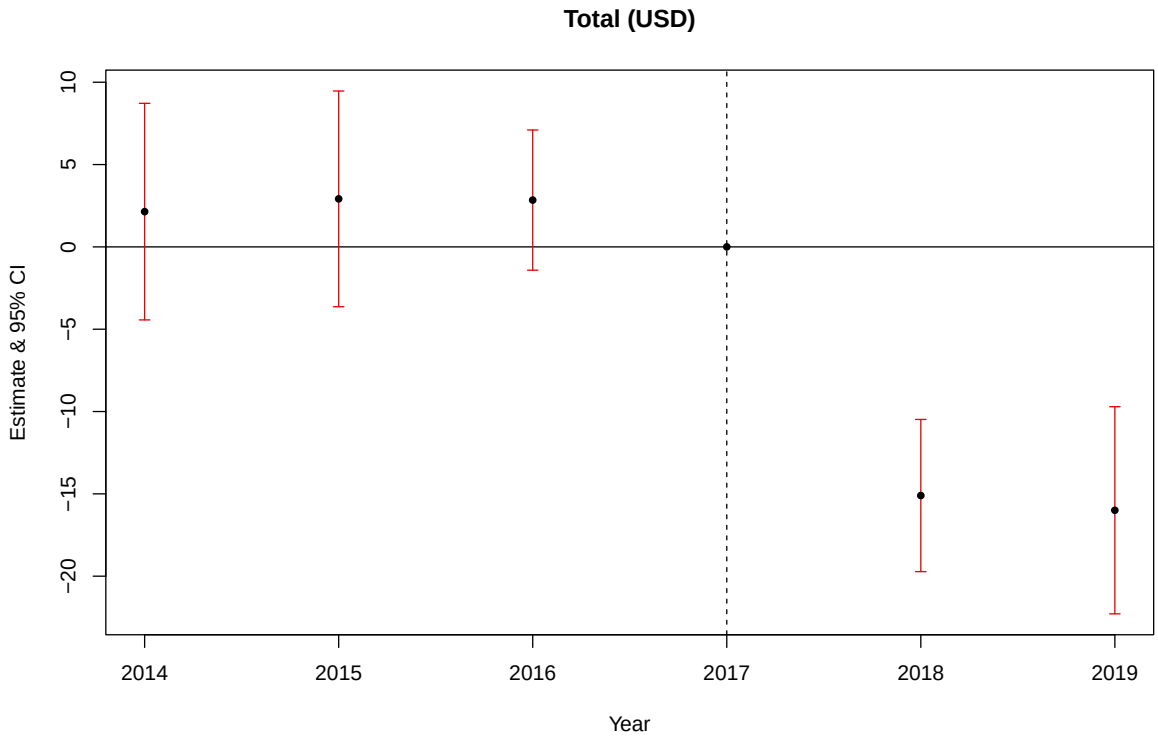
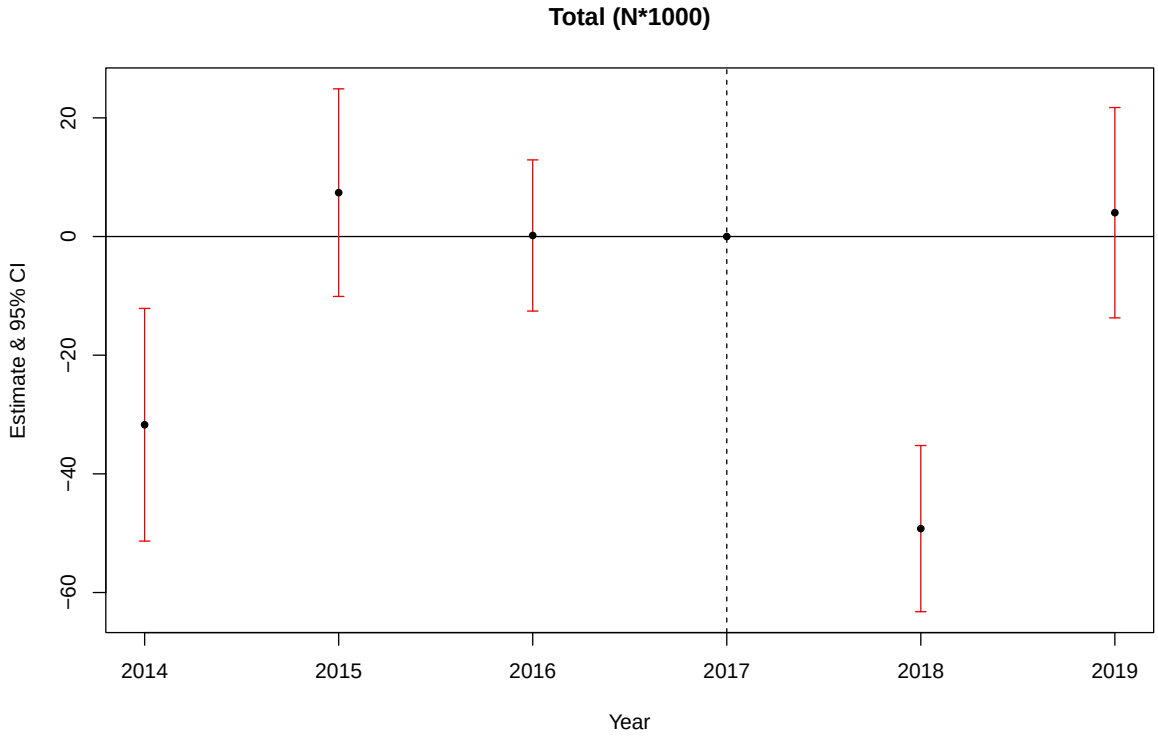



Figure 3: Effect of Policy on Frequency of Industry Payments



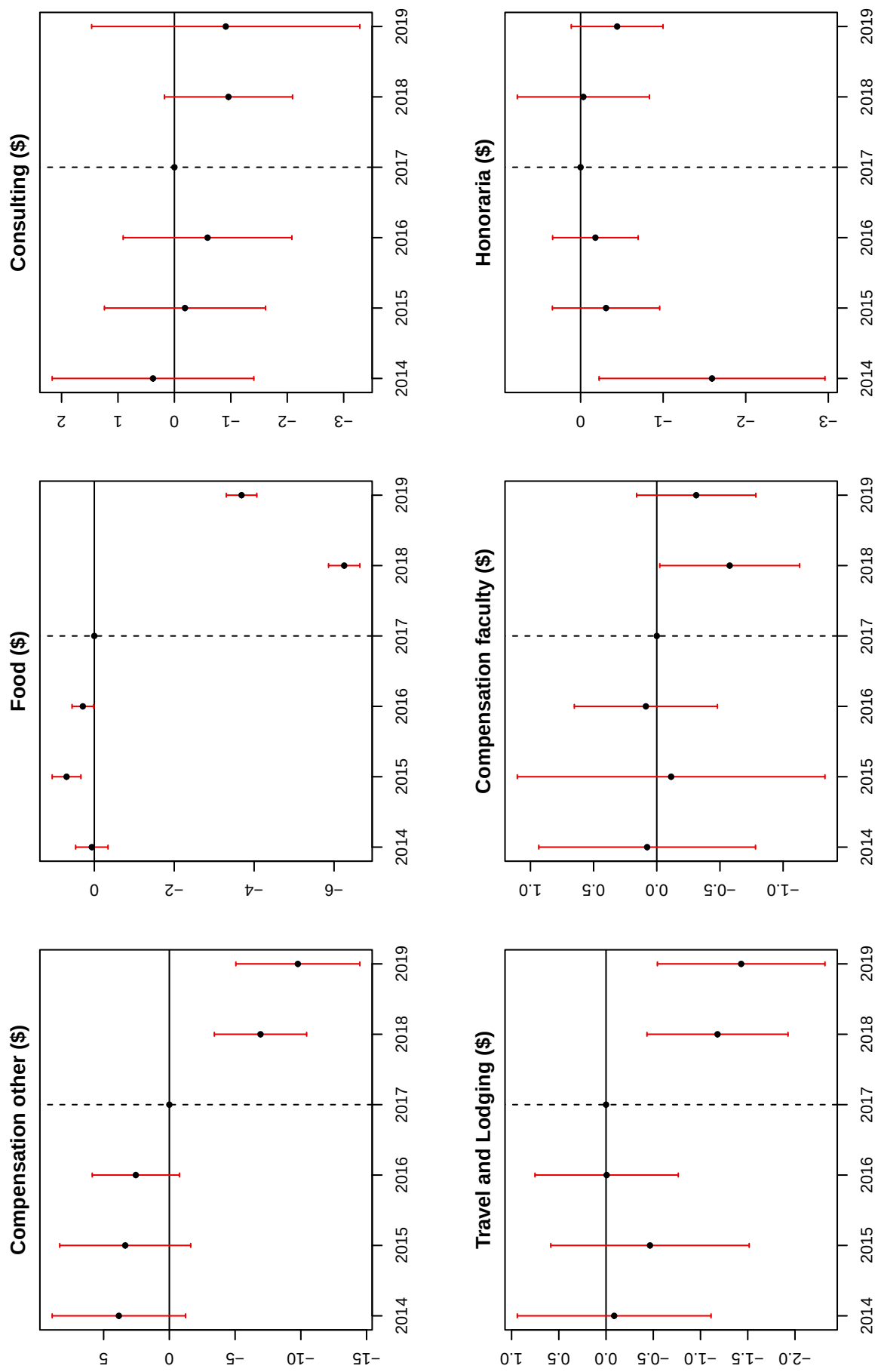



Figure 4: Effect of Policy on Dollar Value of Each Category of Industry Payments

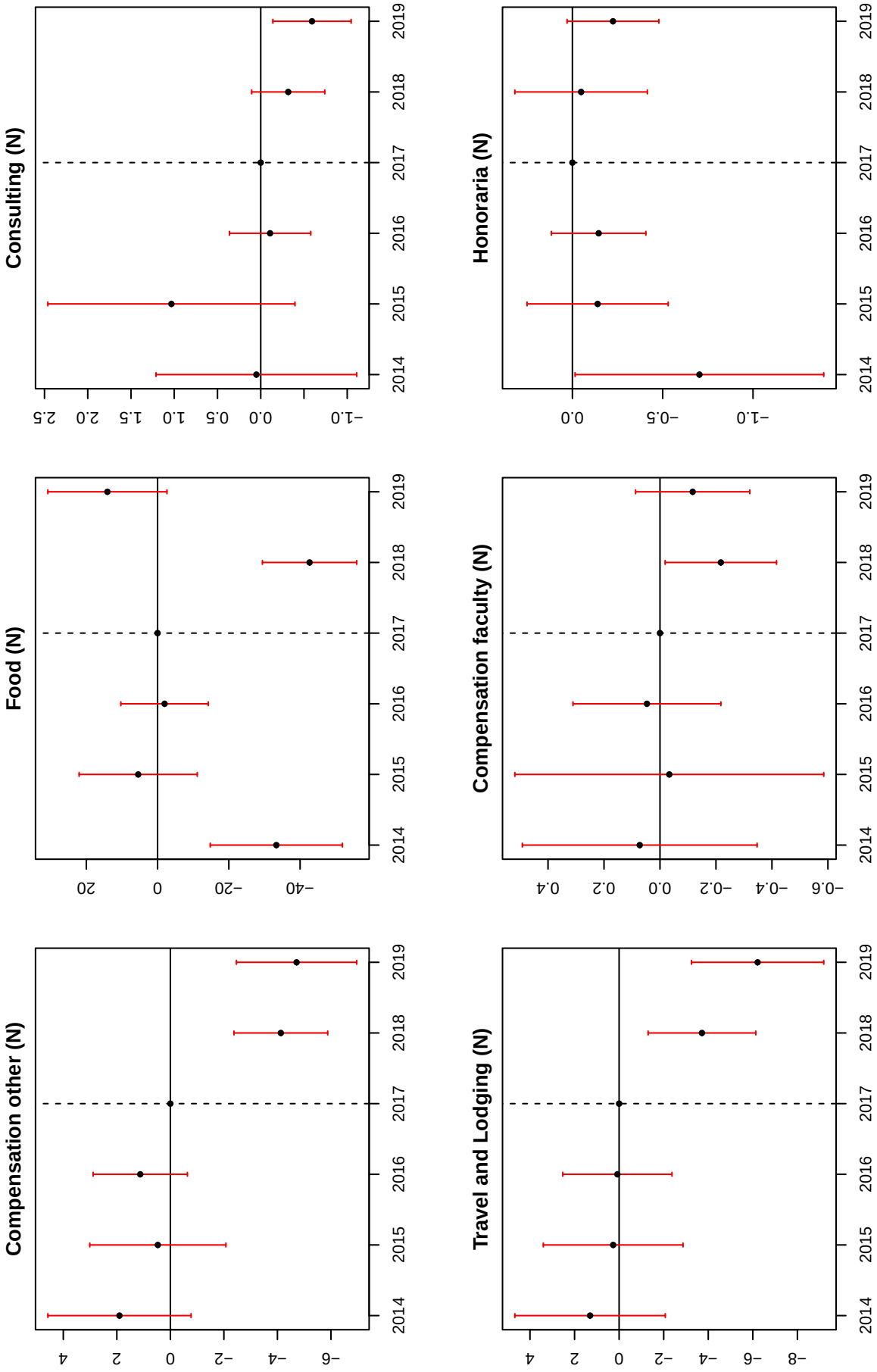



Figure 5: Effect of Policy on Frequency of Each Category of Industry Payments

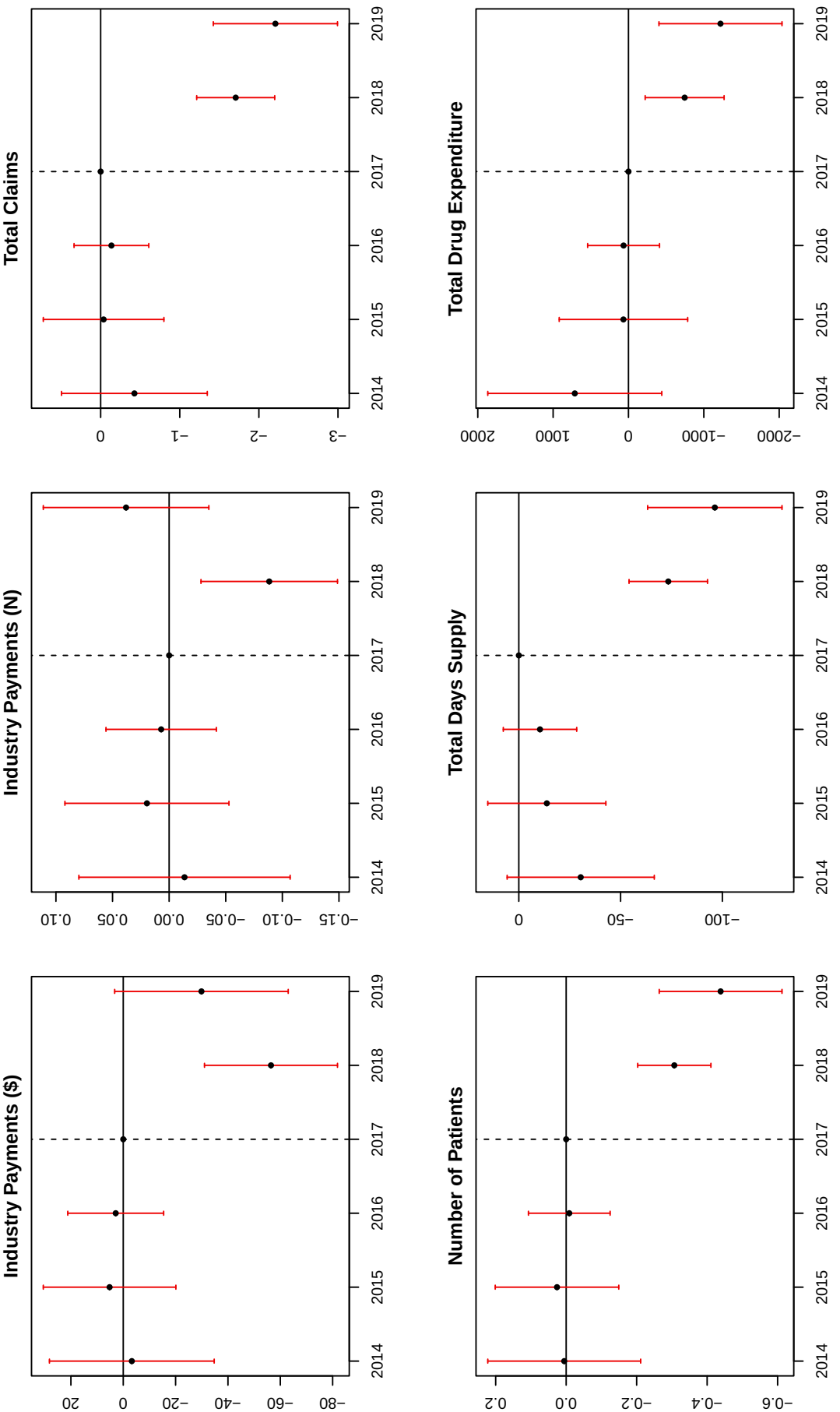



Figure 6: Effect of Policy on Industry Payments, Prescriptions Volume and Cost

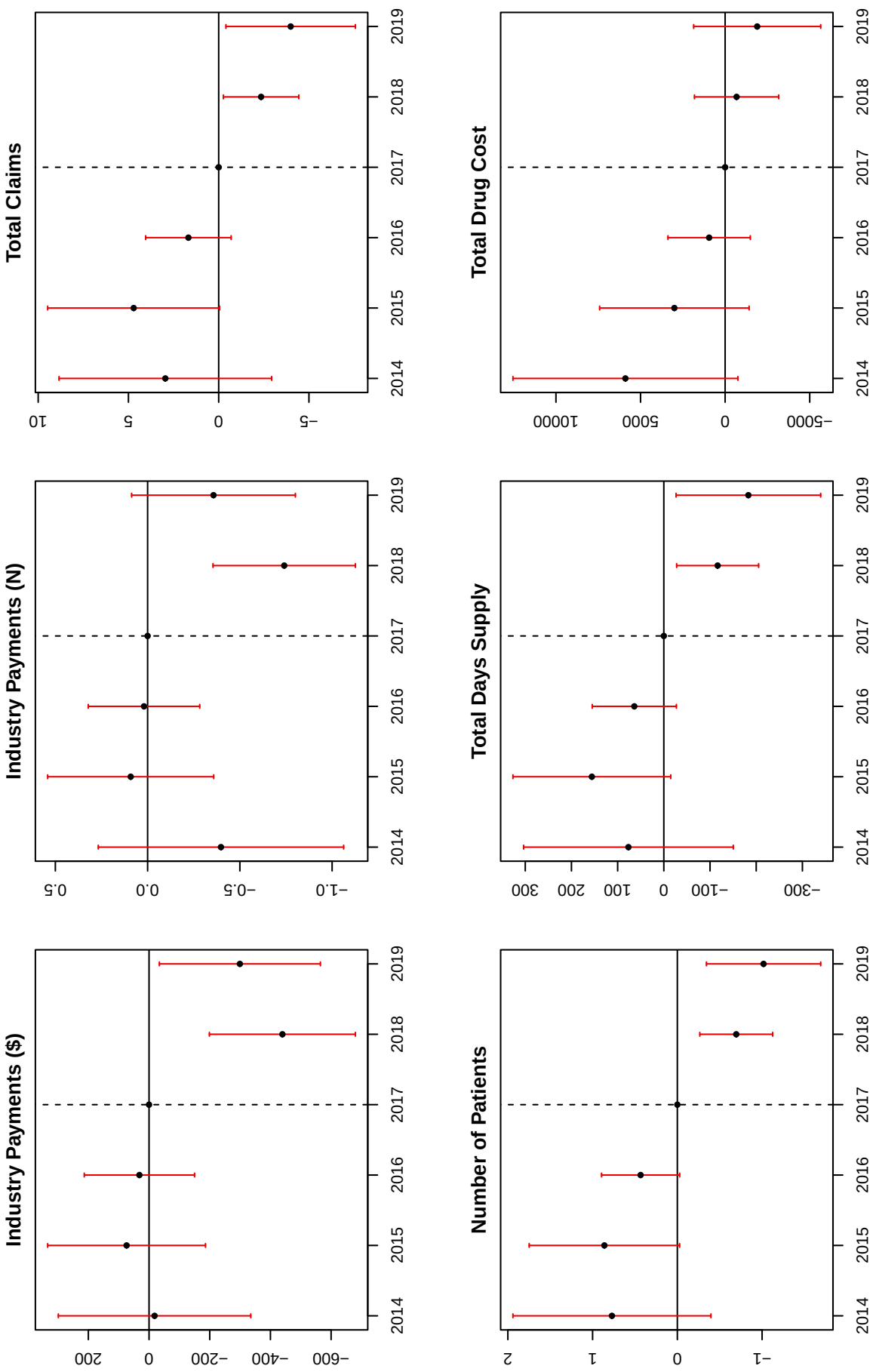



Figure 7: Effect of Policy on Industry Payments, Prescriptions Volume and Cost for Heavy Receivers

Figure 8: Effect of Policy on Industry Payments and Brand Vs. Generic Prescribing

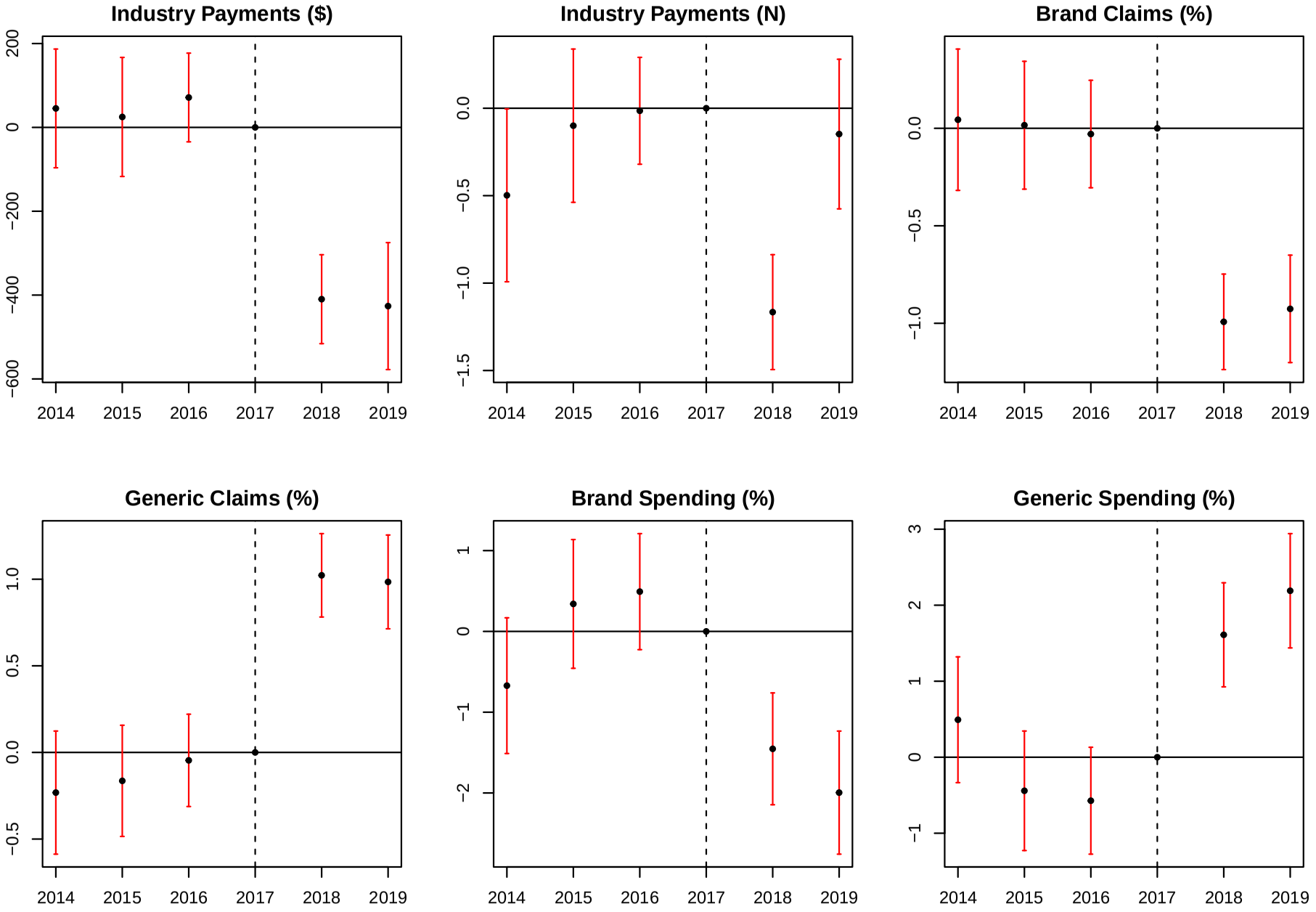


Figure 9: Heterogenous Treatment Effects by Pre-policy Payment Intensity

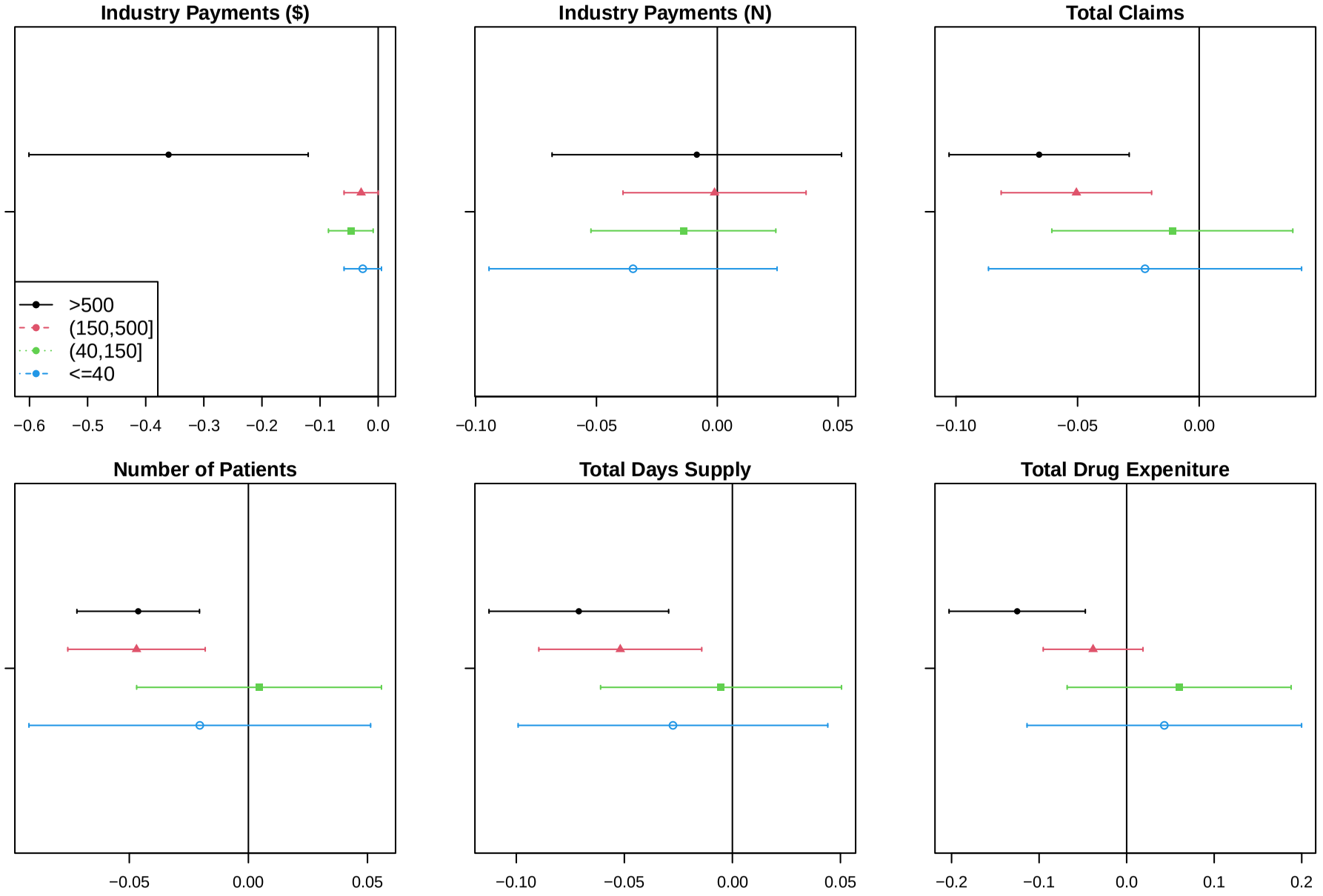


Figure 10: Heterogenous Treatment Effects by Drugs' Age

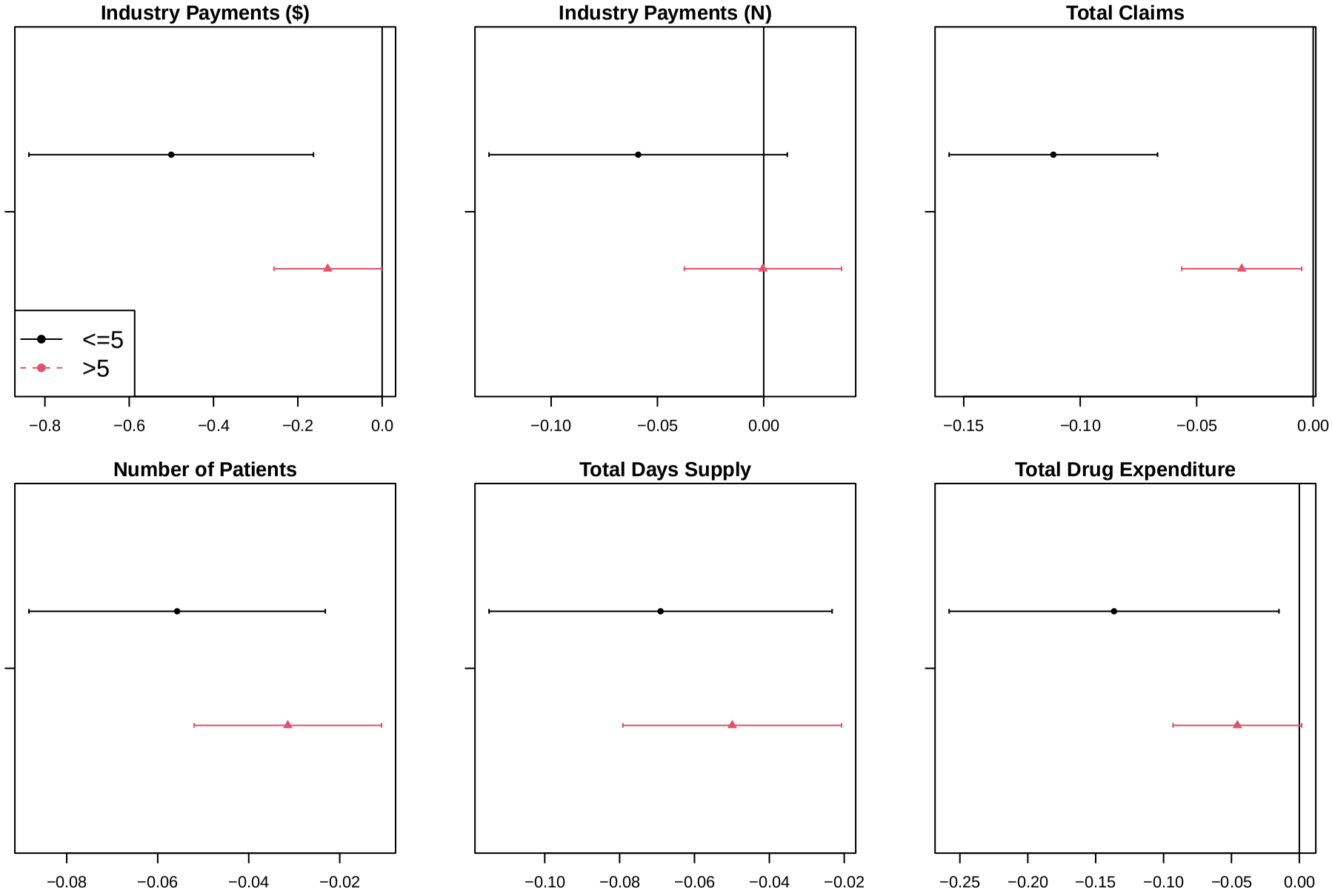


Table 1: Categories of Industry Payment Nationwide (2014-2019)

| | 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 | 535 | 575 | 531 | 652 |
| Number of Physicians | 3,853 | 8,340 | 6,041 | 18,191 |
| Industry Payments ($) | 169.6 | 208.9 | 163.9 | 184 |
| Industry Payments (N) | 1.89 | 1.75 | 1.72 | 1.77 |
| Total Days Supply | 1,389.4 | 1,524 | 1,089 | 1,340 |
| Number of Patients | 10.3 | 11.17 | 8.78 | 10.13 |
| Total Claims | 34.8 | 40.1 | 31.1 | 36.1 |
| Total Drug Cost | 20,764 | 21,935 | 16,550 | 19764.5 |

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 | -17.78*** | -10.83*** | -5.279*** | -0.8478 | -1.183*** | -0.4614 | 0.2673 |
| | (2.925) | (2.113) | (0.1970) | (0.7486) | (0.4120) | (0.2856) | (0.3273) |
| Pre-policy mean | 76.74 | 42.11 | 17.84 | 7.07 | 6.35 | 1.47 | 1.79 |
| ***B: Industry Payments*** ($N \times 1000$) | | | | | | | |
| Treat × Post | -17.32* | -5.325*** | -7.152 | -0.6985** | -5.424*** | -0.1899 | 0.1037 |
| | (8.936) | (1.112) | (8.145) | (0.3452) | (1.414) | (0.1377) | (0.1590) |
| Pre-policy mean | 968 | 23 | 911 | 5 | 24 | 1 | 1 |
| Observations | 5,298,102 | 5,211,269 | 5,215,385 | 5,211,235 | 5,211,268 | 5,211,222 | 5,211,222 |
| No. physicians | 33,334 | 33,334 | 33,334 | 33,334 | 33,334 | 33,334 | 33,334 |

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 | -44.38*** | -0.0285 | -1.808*** | -0.3782*** | -71.25*** | -1,193.4*** |
| | (13.40) | (0.0343) | (0.4145) | (0.0921) | (17.35) | (453.7) |
| *Event study model* | | | | | | |
| | -29.88* | 0.0380 | -2.209*** | -0.4383*** | -96.30*** | -1,221.1*** |
| | (16.91) | (0.0373) | (0.4005) | (0.0889) | (16.84) | (416.6) |
| Year 2018 | -56.45*** | -0.0884*** | -1.707*** | -0.3069*** | -73.43*** | -745.4*** |
| | (12.96) | (0.0308) | (0.2516) | (0.0530) | (9.832) | (267.2) |
| Year 2017 (omitted) | 0 | 0 | 0 | 0 | 0 | 0 |
| Year 2016 | 2.880 | 0.0070 | -0.1360 | -0.0088 | -10.41 | 64.91 |
| | (9.344) | (0.0249) | (0.2410) | (0.0591) | (9.205) | (243.3) |
| Year 2015 | 5.221 | 0.0196 | -0.0372 | 0.0260 | -13.76 | 66.83 |
| | (12.93) | (0.0370) | (0.3890) | (0.0895) | (14.80) | (435.0) |
| Year 2014 | -3.270 | -0.0136 | -0.4267 | 0.0055 | -30.41* | 712.5 |
| | (16.06) | (0.0476) | (0.4699) | (0.1107) | (18.44) | (589.1) |
| Pre-policy mean | 223.92 | 2.16 | 38.83 | 10.97 | 1,430 | 20,068 |
| No. physicians | 18,191 | 18,191 | 18,191 | 18,191 | 18,191 | 18,191 |
| Observations | 1,225,369 | 1,225,369 | 1,225,369 | 1,225,369 | 1,225,369 | 1,225,369 |

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 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 | -453.4*** | -0.5037** | -0.9668*** | 1.114*** | -1.765*** | 2.030*** |
| | (62.10) | (0.2103) | (0.1147) | (0.1127) | (0.2861) | (0.2819) |
| *Event study model* | | | | | | |
| Year 2019 | -426.3*** | -0.1476 | -0.9260*** | 0.9844*** | -1.995*** | 2.190*** |
| | (77.26) | (0.2183) | (0.1406) | (0.1381) | (0.3886) | (0.3836) |
| Year 2018 | -409.8*** | -1.166*** | -0.9925*** | 1.022*** | -1.454*** | 1.610*** |
| | (54.11) | (0.1677) | (0.1250) | (0.1228) | (0.3532) | (0.3491) |
| Year 2017 (omitted) | 0 | 0 | 0 | 0 | 0 | 0 |
| Year 2016 | 71.32 | -0.0146 | -0.0295 | -0.0458 | 0.4923 | -0.5723 |
| | (53.97) | (0.1559) | (0.1406) | (0.1359) | (0.3663) | (0.3586) |
| Year 2015 | 24.90 | -0.0999 | 0.0158 | -0.1641 | 0.3402 | -0.4416 |
| | (72.44) | (0.2236) | (0.1672) | (0.1638) | (0.4065) | (0.4012) |
| Year 2014 | 45.26 | -0.4980** | 0.0439 | -0.2319 | -0.6716 | 0.4929 |
| | (72.23) | (0.2522) | (0.1849) | (0.1813) | (0.4285) | (0.4222) |
| Pre-policy mean | 1,422 | 18.4 | 21 | 79 | 53 | 47 |
| No. physicians | 56,583 | 56,583 | 56,583 | 56,583 | 56,583 | 56,583 |
| Observations | 339,498 | 339,498 | 339,498 | 339,498 | 339,498 | 339,498 |

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

Table 6: Heavy Receivers Vs. Others (2014-2017)

| | Median Doctor (Top 5%) | Median Doctor (Others) |
|---|---|---|
| Payments ($) | 21,371 | 137 |
| Payments (N) | 75.38 | 6.396 |
| Number of Drugs | 196 | 49 |
| Number of Patients | 147.62 | 60 |
| Total Claims | 574.50 | 195 |
| Total Days Supply | 22,438 | 6,832 |
| Total Drug Expenditure ($) | 412,396 | 94,324 |

Table 7: 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 | -391.5*** | -0.4781** | -5.504** | -1.372*** | -223.8** | -4,894.2* |
| | (122.9) | (0.2214) | (2.180) | (0.3946) | (86.86) | (2,643.7) |
| Pre-policy mean | 2369.25 | 7.06 | 67.66 | 17.67 | 2,682 | 56,738 |
| No. physicians | 910 | 910 | 910 | 910 | 910 | 910 |
| Observations | 94,727 | 94,727 | 94,727 | 94,727 | 94,727 | 94,727 |

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 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 | $\leq 40$ | (40 - 150] | (150 - 500] | $> 500$ |
| Number of Doctors in Each Bin | 4,889 | 4,094 | 4,518 | 4,690 |

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

| | $\leq 5$ | $> 5$ |
|---|---|---|
| Number of Observations | 303,174 | 922,195 |
| Number of Doctors | 12,430 | 17,748 |
| Number of Drugs | 253 | 398 |
| Percent of Industry Payments ($) | 37% | 63% |
| Percent of Industry Payments (N) | 29% | 71% |

Table 10: Placebo with Doctors Never Engaged With Drug Firms

| | Total Claims (1) | Number of Patients (2) | Total Days Supply (3) | Total Drug Cost ($) (4) |
|---|---|---|---|---|
| Placebo Estimates | 3.895 | 2.743 | -42.40 | -932.9 |
| | (4.131) | (2.847) | (35.05) | (855.2) |
| Pre-policy mean | 23.93 | 7.43 | 758.88 | 11,112 |
| No. Physicians | 3,786 | 3,786 | 3,786 | 3,786 |
| Observations | 372,019 | 372,019 | 372,019 | 372,019 |
| Actual Estimates | -1.808*** | -0.3782*** | -71.25*** | -1,193.4*** |
| | (0.4145) | (0.0921) | (17.35) | (453.7) |
| Pre-policy mean | 38.83 | 10.97 | 1,430 | 20,068 |
| No. Physicians | 18,191 | 18,191 | 18,191 | 18,191 |
| Observations | 1,225,369 | 1,225,369 | 1,225,369 | 1,225,369 |

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%.

# Appendix

Hamidreza Habibi

November 3, 2024

## 1 Matching

### 1.1 Optimal Full Matching

While the difference-in-differences design requires the treatment and control units to have similar trends in the absence of the intervention, matching on physicians' characteristics ensures a more robust comparison. Therefore, to enhance the rigor of the comparison, an optimal full-matching approach was implemented using the MatchIt package in R, which calls functions from the optmatch package (Hansen, 2004; Hansen and Klopfer, 2006; Stuart et al., 2011). The optimal full matching algorithm is a form of subclassification that assigns each treated and control unit to subclasses to minimize within-subclass differences.The matching is optimal in the sense that that sum of the absolute distances between the treated and control units in each subclass is as small as possible. The matching literature offers several advantages for optimal full matching compared to nearest neighbor methods.

- Full matching uses all individuals and leads to better matched samples using propensity score, Euclidean or Mahalanobis as distance measures.
- Since calculating a propensity score of being in New Jersey does not make sense for my study, I used scaled Euclidean as my distance measure. Unscaled Euclidean distances are sensitive to scale of the variables. (like synthetic control)
- Each subclass contains one treated unit and one or more control units or one control units and one or more treated units.

- It is optimal in the sense that the chosen number of subclasses and the assignment of units to subclasses minimize the sum of the absolute within-subclass distances in the matched sample.

To explain the matching algorithm and compare it with nearest neighbor methods, consider the following hypothetical data for both control and treated observations. The optimal full matching method clearly outperforms others in minimizing distance while retaining all observations.

| Treated | | Control | |
|---|---|---|---|
| Doctors | Prescription Volume | Doctors | Prescription Volume |
| A | 42 | a | 44 |
| B | 35 | b | 42 |
| C | 24 | c | 37 |
| D | 22 | d | 34 |
| | | e | 23 |

- Nearest Neighbor Matching (greedy):
  {Ab}, {Bd}, {Ce}, and {Dc}. Yields a global distance of 17 (0+1+1+15).
  (e remains unmatched)

- Optimal Nearest Neighbor Matching:
  Order is not important.
  {Ab}, {Bc}, {Cd}, and {De}. Yields a global distance of 13 (0+2+10+1).

- Optimal Full Matching:
  {Aab}, {Bcd}, and {CDe}. Yields a global distance of 7 (2+0+2+1+1+1).

## 1.2 Matching Variables and Weight Construction

Table 1 outlines the variables used for matching in each part of the analysis. This study implements exact matching on medical specialty and optimal full matching using scaled Euclidean distance on all other variables, based on pre-policy data.

For the first stage analysis, I implement exact matching on specialty and distance matching on beneficiary risk score and the number of distinct drugs. For the reduced form analysis, in addition to the previous variables, I also match doctors on pre-policy levels of payments they received from pharmaceutical firms (i.e. pre-policy outcomes in the first

stage). For the branded-generic analysis, since the drug-level data is not available, the variables used for matching do not include the number of distinct drugs and the number of patients. Instead, physicians' proportion of brand claims in the pre-policy period is used to ensure a rigorous comparison.

Table 1: Variables Used for Matching in Each Section

| Variables | First Stage (Section 5.1) | Reduced Form (Sections 5.2-5.4) | Brand Vs. Generic (Section 5.3) |
|---|---|---|---|
| Medical Specialty | ✓ | ✓ | ✓ |
| Beneficiary Risk Score | ✓ | ✓ | ✓ |
| Number of Distinct Drugs | ✓ | ✓ | |
| Industry Payments ($) | | ✓ | ✓ |
| Industry Payments (N) | | ✓ | ✓ |
| Number of Patients | | ✓ | |
| Proportion of Brand Claims | | | ✓ |

After assigning each doctor to subclasses based on the matching variables, a subclass propensity score ($s_p$) is calculated as the number of treated doctors in each subclass ($N_T^S$) divided by the total number of doctors in each subclass ($N^S$):

$$s_p = \frac{N_T^S}{N^S} \tag{1}$$

Then, a weight equal to 1 is assigned to treated units and a weight of $\frac{s_p}{1-s_p}$ is assigned to control units in each stratum. In addition, control units' weights in each subclass are scaled by the number of control units ($N_C$) divided by the number of treated units ($N_T$) in the overall sample. Therefore, the weights for each individual treated doctor in each subclass is 1, and for each control doctor, it is $\frac{s_p}{1-s_p}\frac{N_C}{N_T}$.

Figures 1 and 2 show the absolute standardized mean difference between covariates after and before matching. While even before matching most of the covariates show balance, the standardized mean difference between all covariates becomes smaller than 0.05. [1]

[1] While most studies use 0.1 as the significant threshold, I used 0.05 to be more rigorous.

Figure 1: Definitions for Each Category of Payment

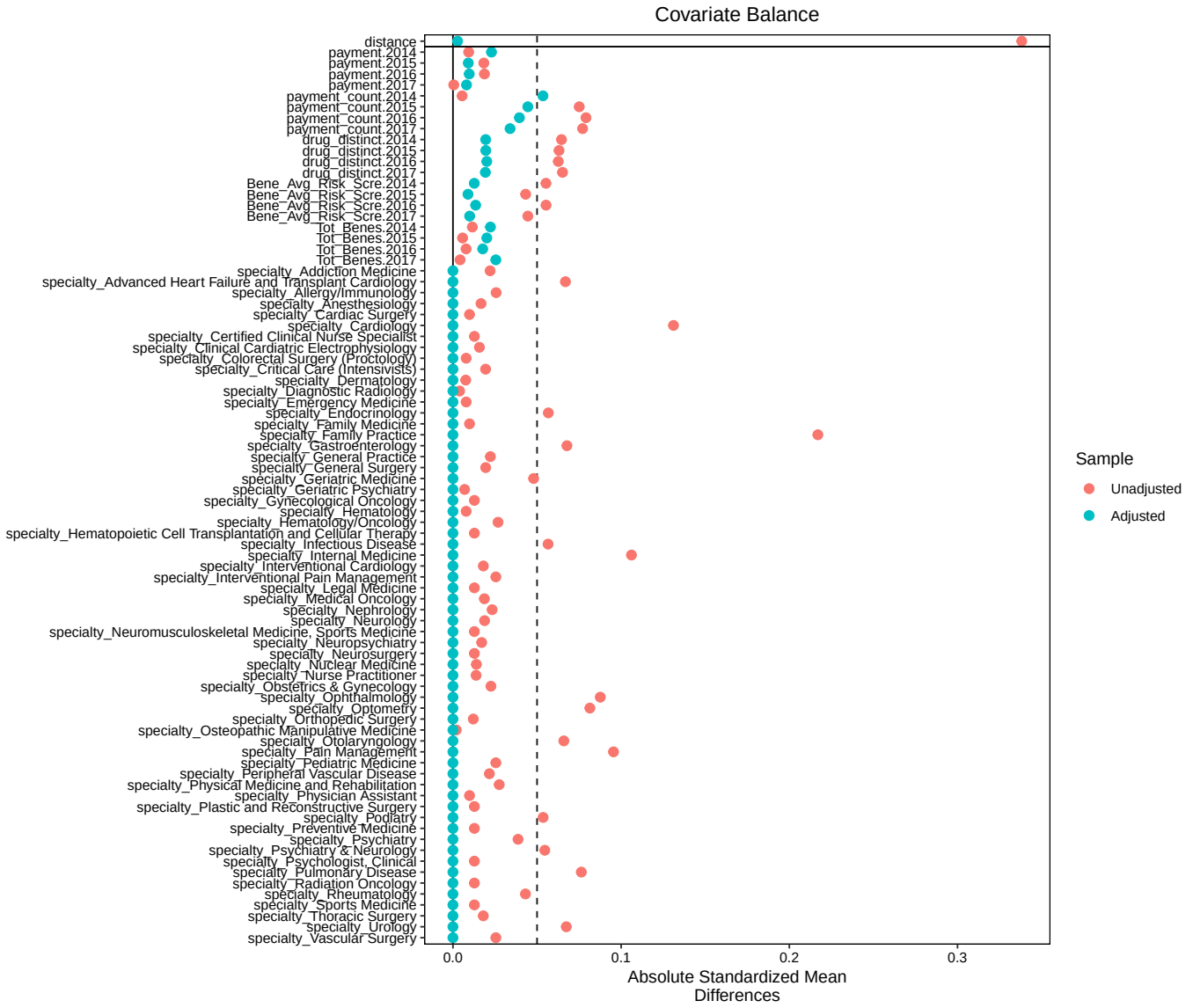
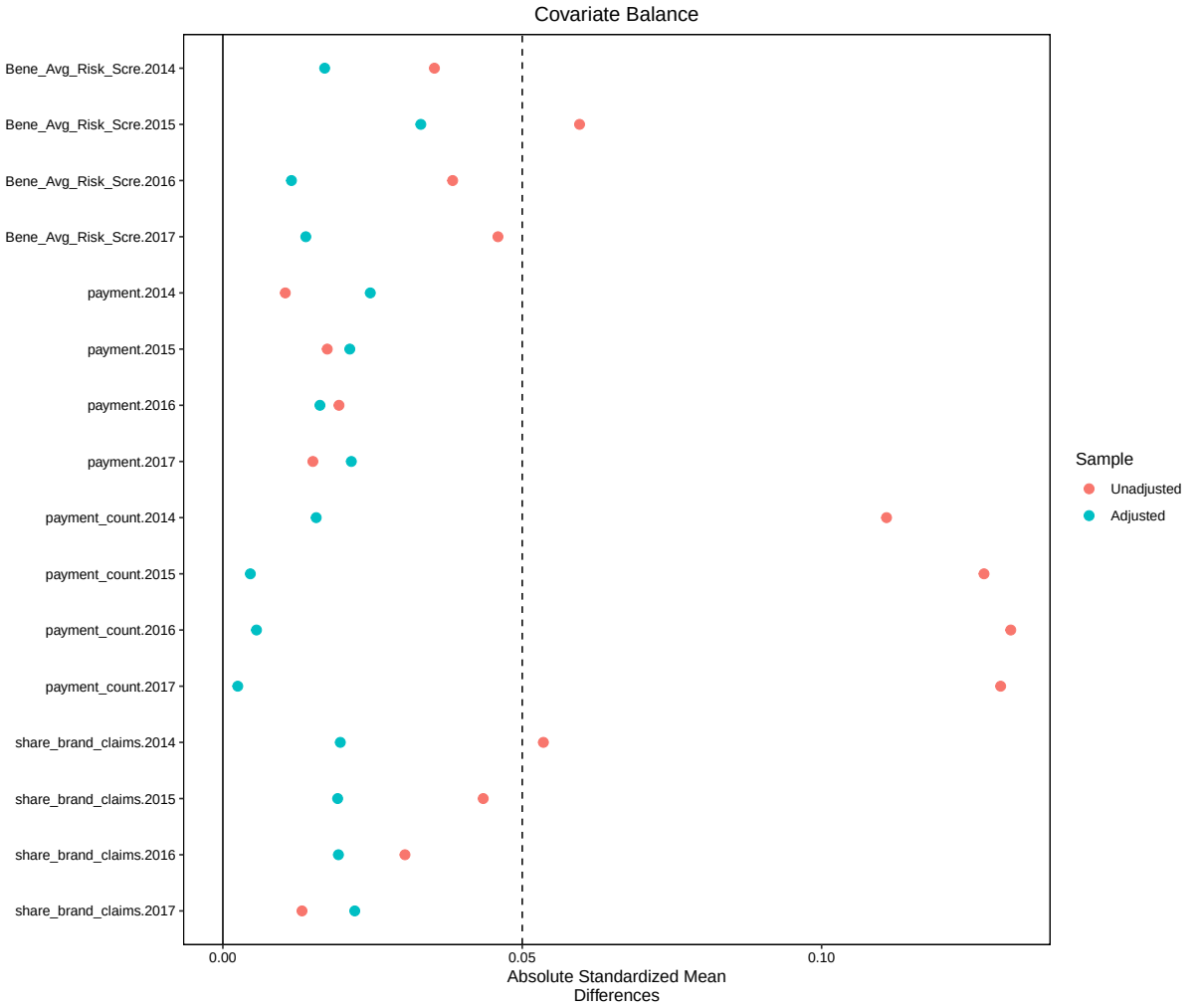


Figure 2: Definitions for Each Category of Payment



# 2 Event Study Estimates for Heterogeneity Analyses

In the main analysis, I only report the average DiD estimates for the heterogeneity analysis. Figures 3 and 4 show that the DiD estimates reported in the main analysis are not driven by differential pre-trends.

Figure 3: Event Study Figures: Heterogeneity by Payment Intensity

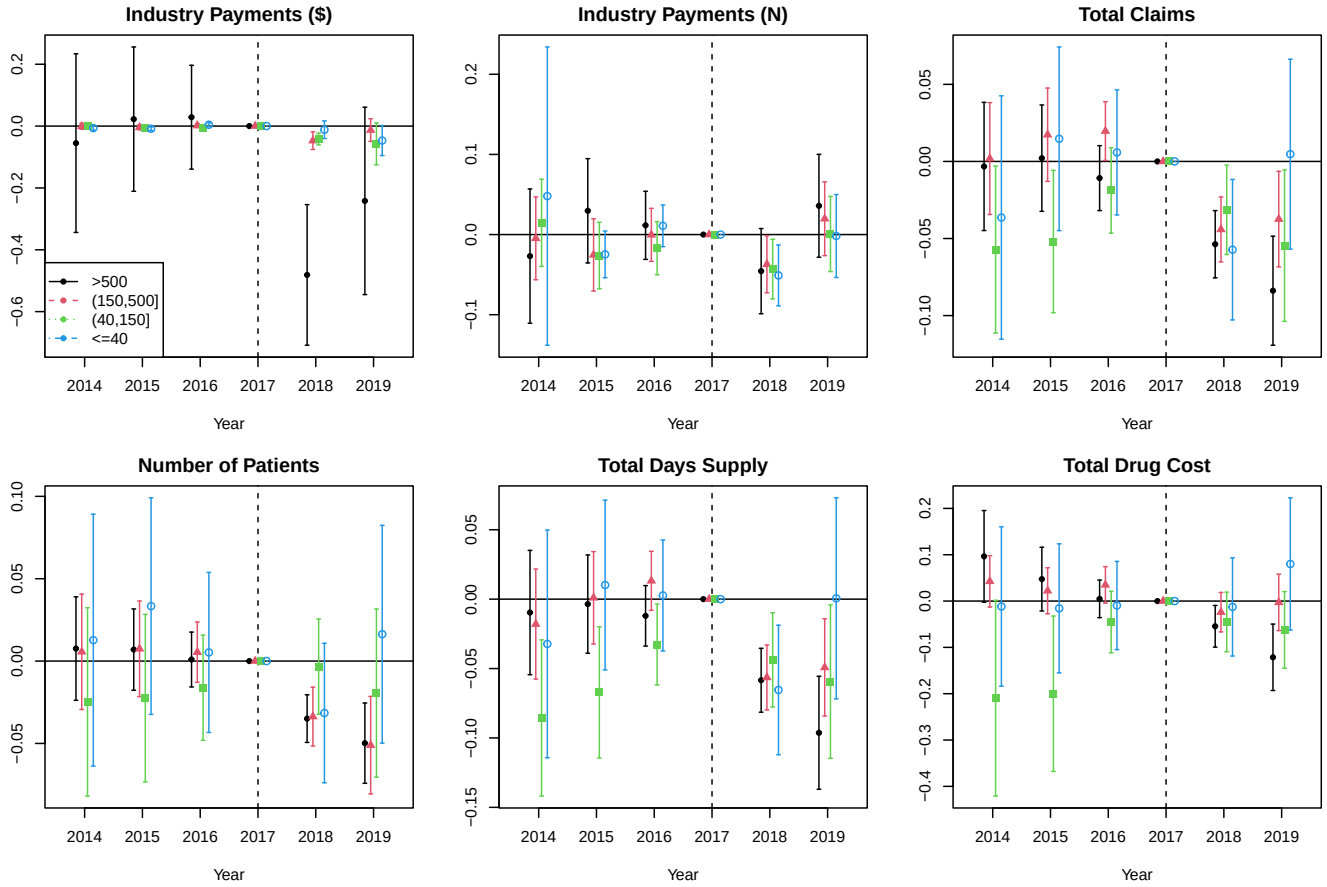
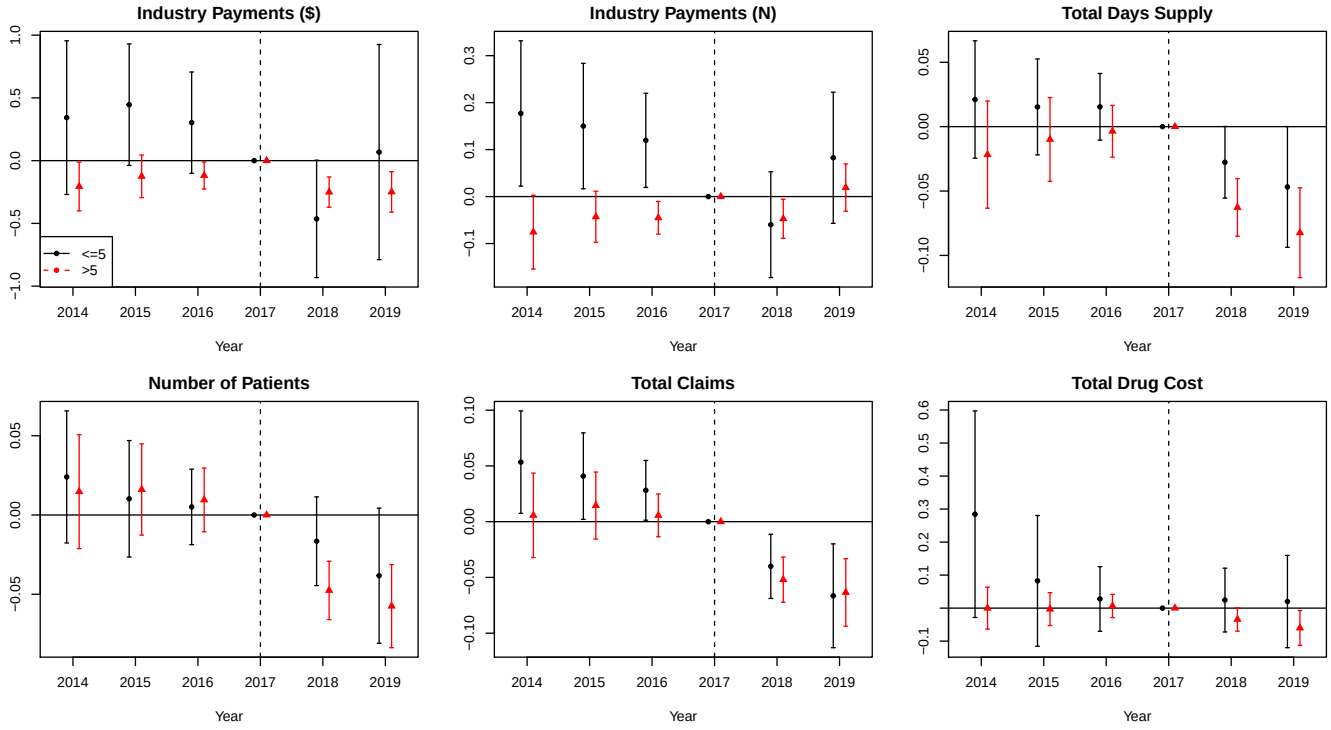


Figure 4: Event Study Figures: Heterogeneity by Drugs' Age




# 3 Synthetic Control

I utilize the synthetic control method developed by Abadie et al. (2010) to create a counterfactual post-treatment path for New Jersey [2]. Let the index $i = (0, 1, ..., I)$ denote US states. Where $i = 0$ corresponds to New jersey and $i = (1, ..., I)$ correspond to other states in the control group (donor pool). Define $G_0$ as a $k \times 1$ vector with elements equal to the predictive variables plus dependent variables in each month from January 2016 through December 2017 (i.e preintervention period) for New Jersey. Also, define $k \times I$ matrix $G_1$ as the same data vectors for other I states in the donor pool. Using an optimization process developed by Abadie et al. (2010), the synthetic control method identifies a convex combination of the $I$ states in the donor pool that best explains the preintervention data vector for treated state. Define $I \times 1$ weighting vector $W = (w_1, w_2, ..., w_I)$ such that $\sum_{i=1}^{I} W_i = 1$, and $w_i \geq 0$ for $i = (1, ..., I)$. The product $G_1 W$ gives a weighted average of the preintervention vectors for all states in donor pool excluding the treated state, with the difference between the treated state and this treated state is given by $G_0 - G_1 W$.Synthetic control finds the best weighting vector,W, that can

[2] I use Bohn et al. (2014) to frame this part.

create the best approximation path for treated state in preintervention period. This weighting vector is chosen by solving the constrained quadratic minimization problem:

$$
\begin{aligned}
& W^* = \underset{W}{\operatorname{argmin}} (G_0 - G_1 W)' V (G_0 - G_1 W) \\
& s.t. \\
& W_i' = 1, \qquad w_i \geq 0, \qquad i = (1, ..., I),
\end{aligned}
\tag{2}
$$

where $V$ is a $k \times k$ diagonal positive-definite matrix with diagonal elements being the relative weights. After obtaining an optimal weighting vector, $W^*$, both paths for preintervention and postintervention values for dependent variables in "synthetic NJ" can be tabulated by calculating the corresponding weighted average for each month using the donor states with positive weights. The postintervention values for the synthetic control group serve as counterfactual outcomes for New Jersey. In addition to the average of the dependent variables themselves, I include the average physician per capita in each state over the preintervention period as an important predictor variable.[3] The main estimate of the treatment effect can be calculated using a simple difference in difference method using the difference in the mean of the dependent variables between the treated and control state after and before the intervention. Equation 1.2 shows the DID estimation formula:

$$
\begin{aligned}
DD_{NJ} =& (Outcome^{NJ}_{post} - Outcome^{synthetic}_{post}) \\
& - (Outcome^{NJ}_{pre} - Outcome^{synthetic}_{pre})
\end{aligned}
\tag{3}
$$

I expect to see a negative estimate ($DD_{NJ} \leq 0$) because the laws were designed to reduce firm-doctor interactions. Following Abadie et al. (2010), I apply the permutation test (placebo test) to DID estimator in equation 1.2. Specifically, the same analysis is conducted for each state in the donor pool as if these states had enacted similar restrictions at the same time to avoid some spurious regression results. To show the

[3]Other predictive variables can be added later, but since treatment effect is substantial even without a rich set of covariates, I anticipate adding more predictive variables will not affect the results significantly.

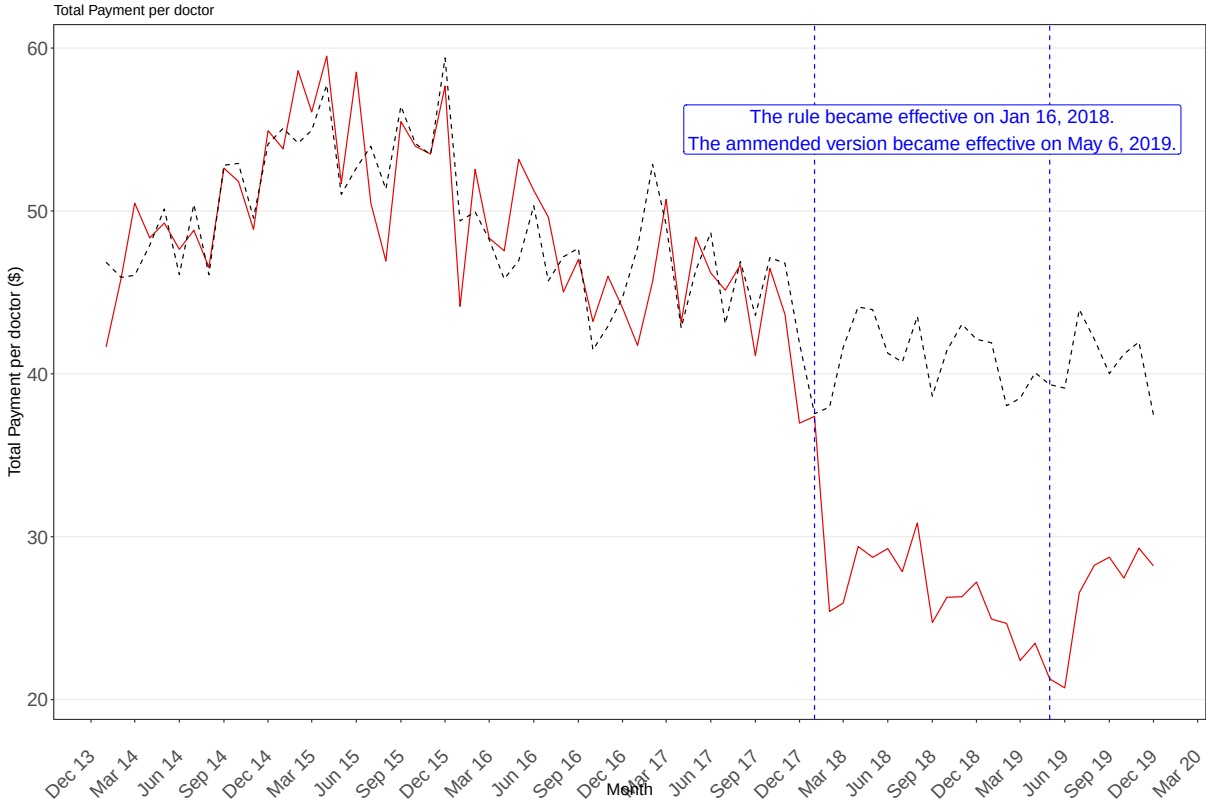
results are not driven by chance, we need to see the drop only in the treated states and should not observe any visible effect in the paths in other states at the time of intervention.

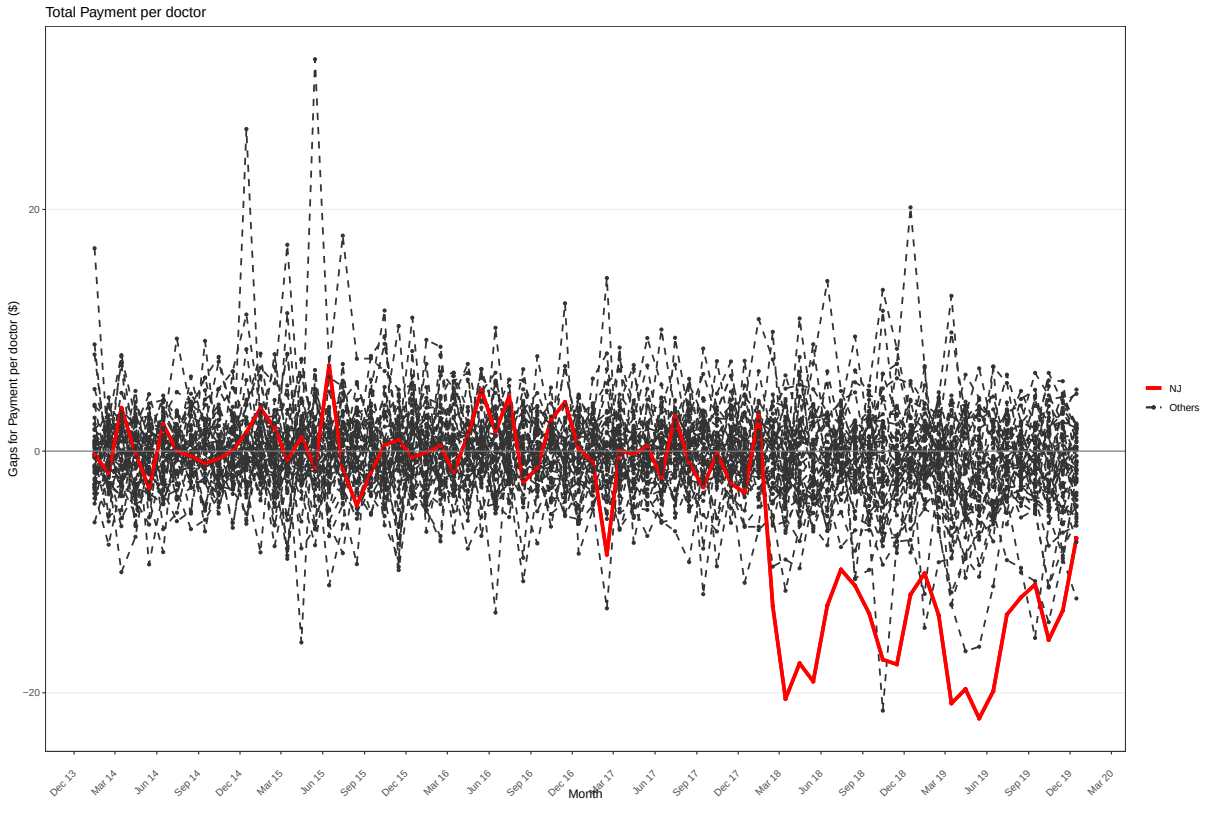
In addition to the lags of each outcome, I used the following variables to fit the synthetic control:

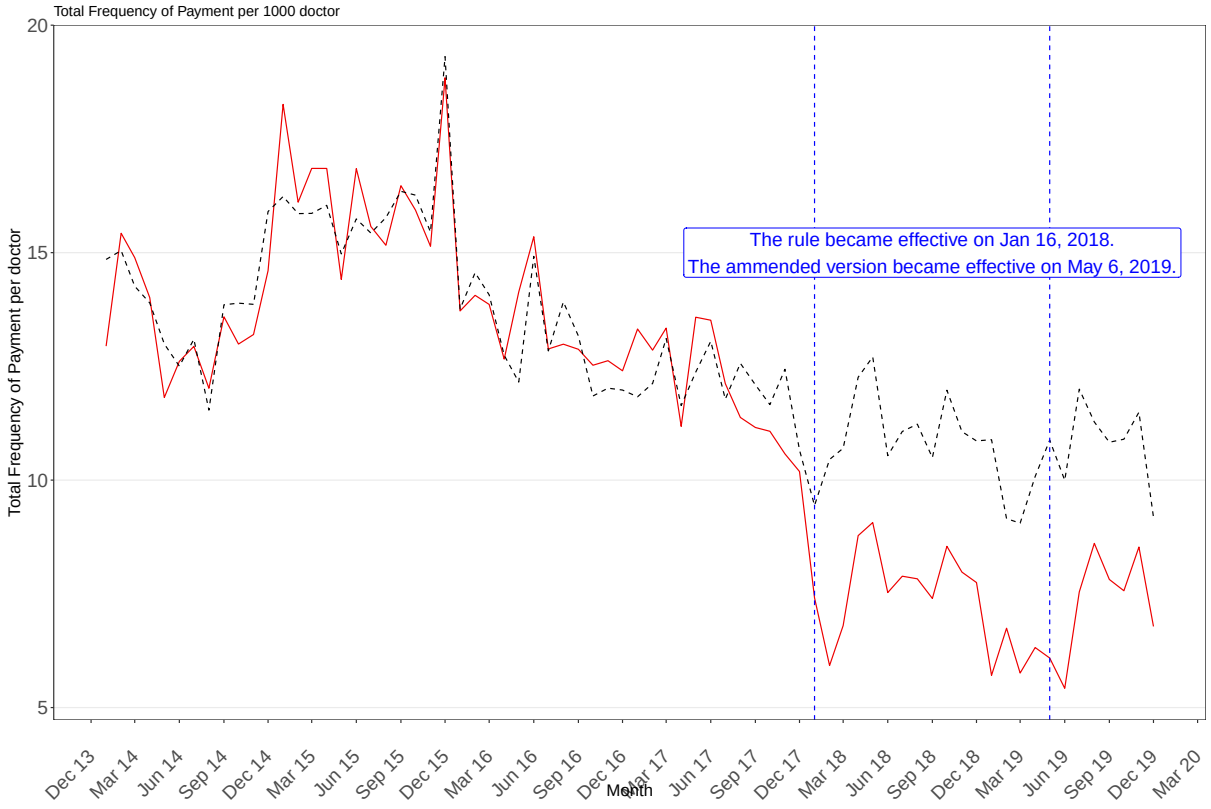
Figure 5: Synthetic Control Variables

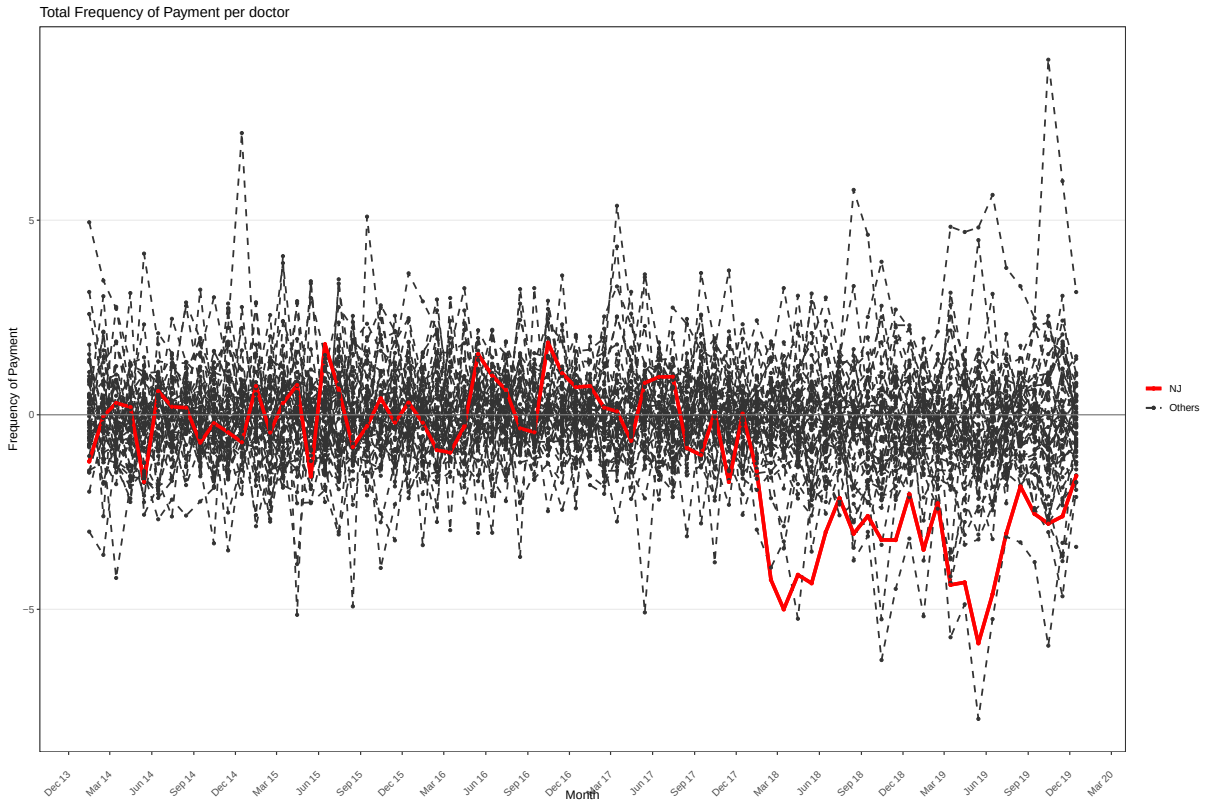
| Number | Variables |
|---|---|
| 1 | Beneficiary Average Risk Score |
| 2 | Proportion of Male doctors |
| 3 | Share of population with Medicare |
| 4 | Share of Population with Good or Excellent health |
| 5 | Average Experience of Prescribers |
| 6 | Proportion of Doctors in 50 specialties with highest drug costs and claims |
| 7 | Share of Population in Poverty |
| 8 | GDP Per Capita |
| 9 | Medicare Spending for prescription drugs per enrollee |
| 10 | Number of Part D enrollee per Doctor |

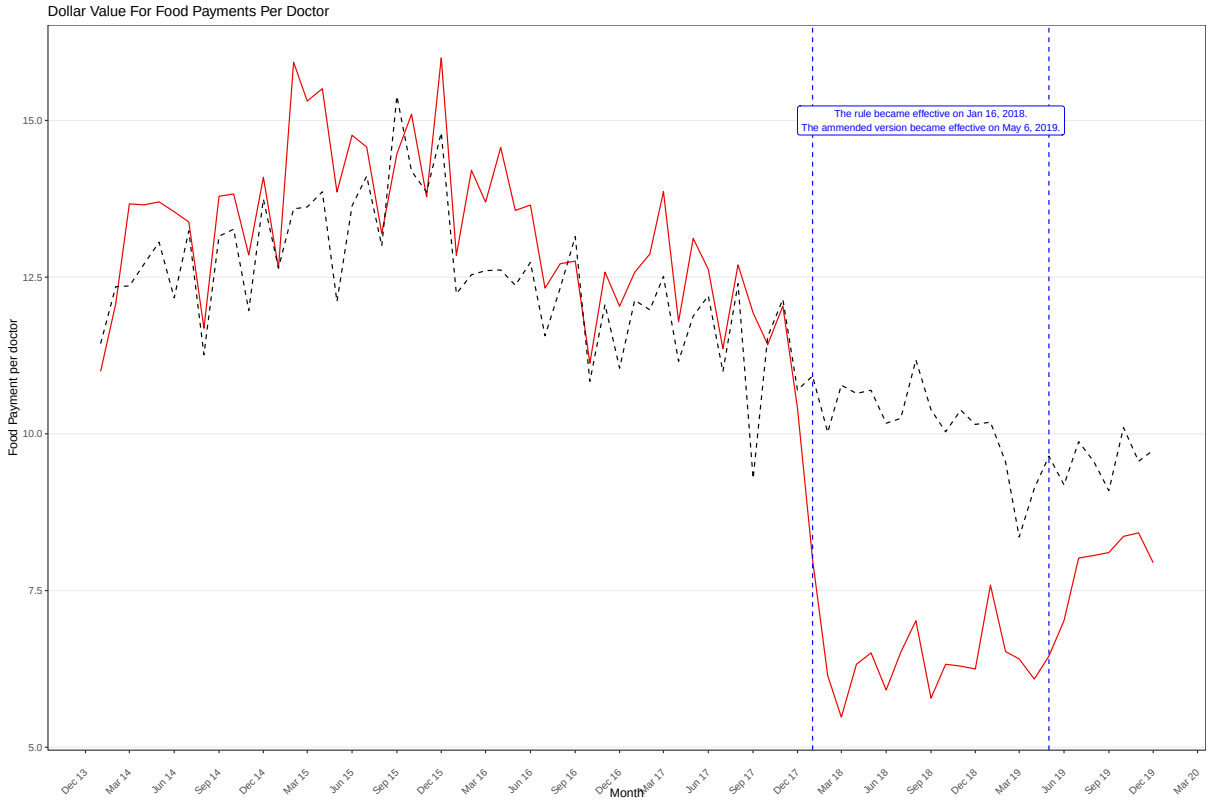
## 3.1 Synthetic Control: First Stage Results




Total Frequency of Payment per 1000 doctor
Total Frequency of Payment per doctor
20
15
10
5
The rule became effective on Jan 16, 2018.
The ammended version became effective on May 6, 2019.
Dec 13
Mar 14
Jun 14
Sep 14
Dec 14
Mar 15
Jun 15
Sep 15
Dec 15
Mar 16
Jun 16
Sep 16
Dec 16
Mar 17
Jun 17
Sep 17
Dec 17
Mar 18
Jun 18
Sep 18
Dec 18
Mar 19
Jun 19
Sep 19
Dec 19
Mar 20
Month


Total Frequency of Payment per doctor
Frequency of Payment
5
0
−5
NJ
Others
Dec 13
Mar 14
Jun 14
Sep 14
Dec 14
Mar 15
Jun 15
Sep 15
Dec 15
Mar 16
Jun 16
Sep 16
Dec 16
Mar 17
Jun 17
Sep 17
Dec 17
Mar 18
Jun 18
Sep 18
Dec 18
Mar 19
Jun 19
Sep 19
Dec 19
Mar 20
Month


Dollar Value For Food Payments Per Doctor
The rule became effective on Jan 16, 2018.
The ammended version became effective on May 6, 2019.
Food Payment per doctor
15.0
12.5
10.0
7.5
5.0
Dec 13
Mar 14
Jun 14
Sep 14
Dec 14
Mar 15
Jun 15
Sep 15
Dec 15
Mar 16
Jun 16
Sep 16
Dec 16
Mar 17
Jun 17
Sep 17
Dec 17
Mar 18
Jun 18
Sep 18
Dec 18
Mar 19
Jun 19
Sep 19
Dec 19
Mar 20
Month

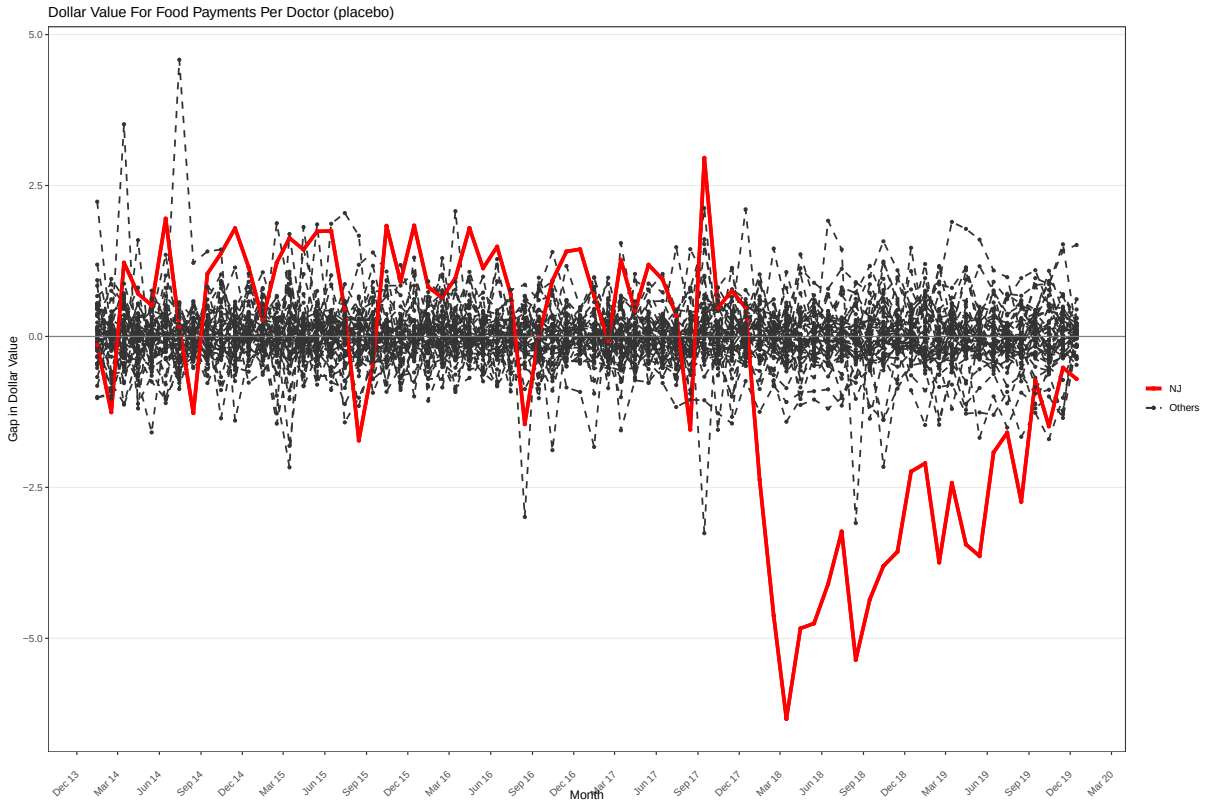
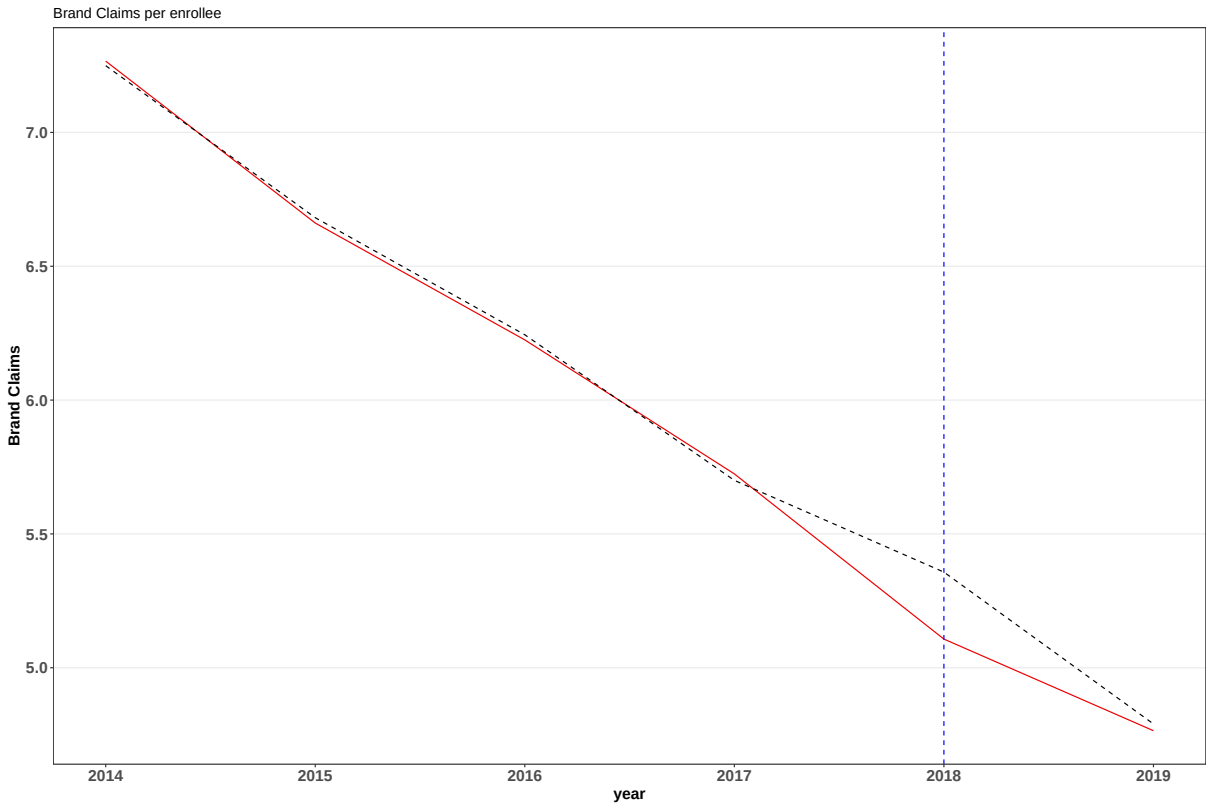
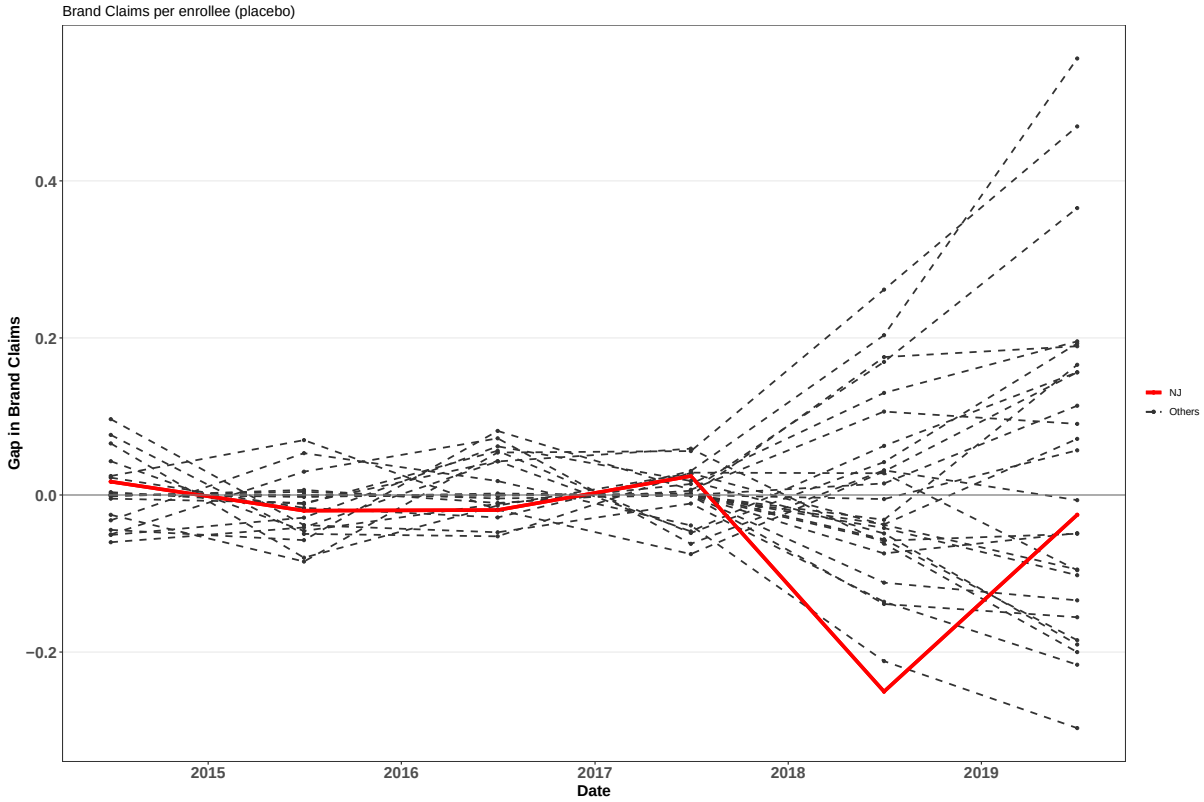

Dollar Value For Food Payments Per Doctor (placebo)
Gap in Dollar Value
5.0
2.5
0.0
−2.5
−5.0
Dec 13
Mar 14
Jun 14
Sep 14
Dec 14
Mar 15
Jun 15
Sep 15
Dec 15
Mar 16
Jun 16
Sep 16
Dec 16
Mar 17
Jun 17
Sep 17
Dec 17
Mar 18
Jun 18
Sep 18
Dec 18
Mar 19
Jun 19
Sep 19
Dec 19
Mar 20
Month
NJ
Others

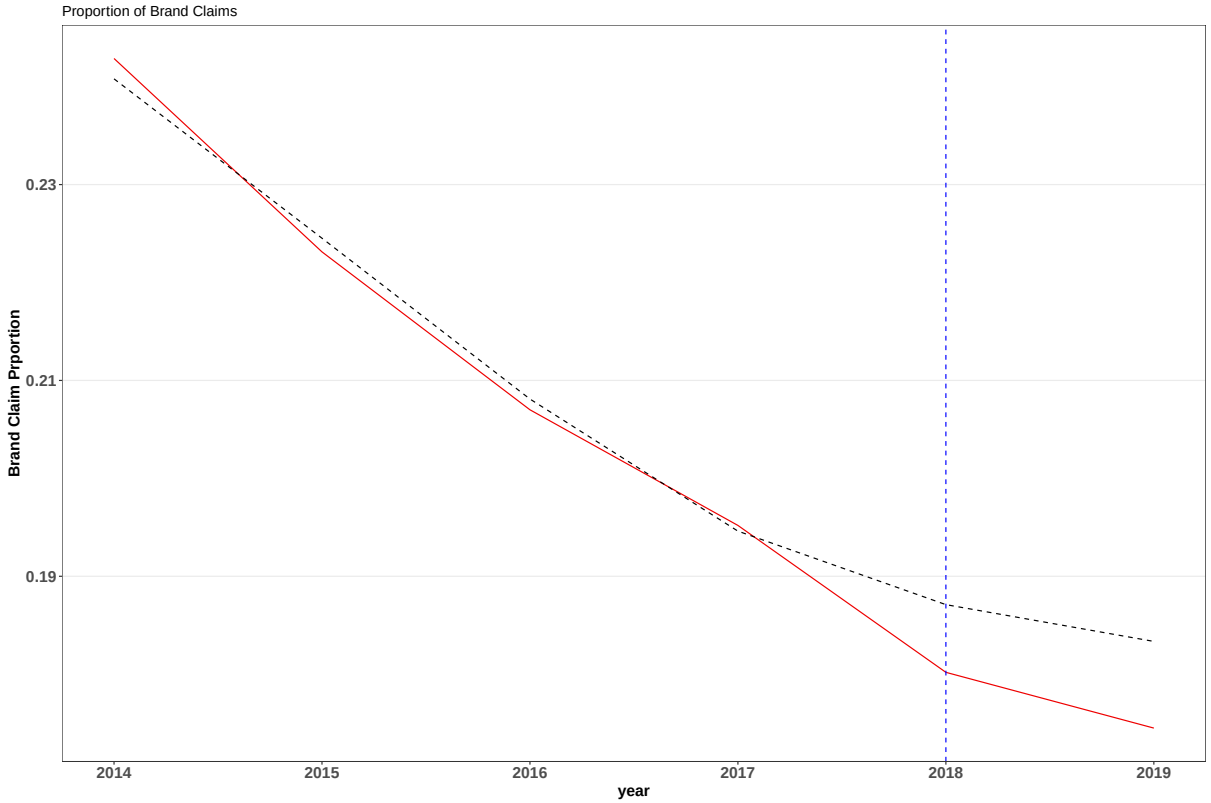
Table 2: Effect of Policy on Value and Frequency of Payments

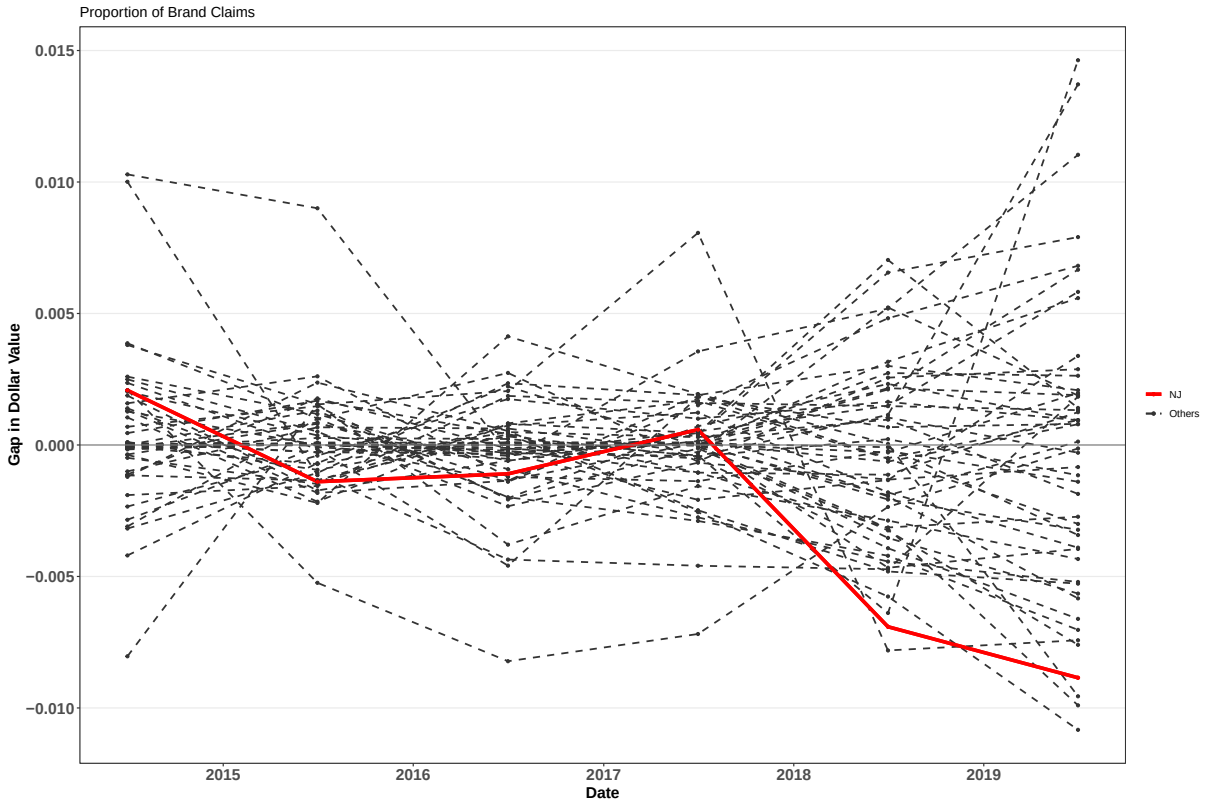
| | Estimate | P-Value | Sample Mean | NJ Rank |
|---|---|---|---|---|
| Total Payment | -14.16 | 0.02 | 48.98 | 1/51 |
| Total Frequency | -3.27 | 0.04 | 13.79 | 2/51 |
| *Dollar Value Per Doctor* | | | | |
| Food | -3.86 | 0.02 | 13.23 | 1/51 |
| Travel | -1.18 | 0.02 | 3.5 | 1/51 |
| Compensation Other | -8.82 | 0.02 | 24.7 | 1/51 |
| Consulting | -1.58 | 0.098 | 6.3 | 5/51 |
| Honoraria | -0.26 | 0.137 | 1.52 | 7/51 |
| *Frequency Per 1000 Doctors* | | | | |
| Food | -7.94 | 0.373 | 637.07 | 19/51 |
| Travel | -4.08 | 0.039 | 14.4 | 2/51 |
| Compensation Other | -3.27 | 0.039 | 13.79 | 2/51 |
| Consulting | -0.69 | 0.039 | 3.73 | 2/51 |
| Honoraria | -0.16 | 0.098 | 0.88 | 5/51 |

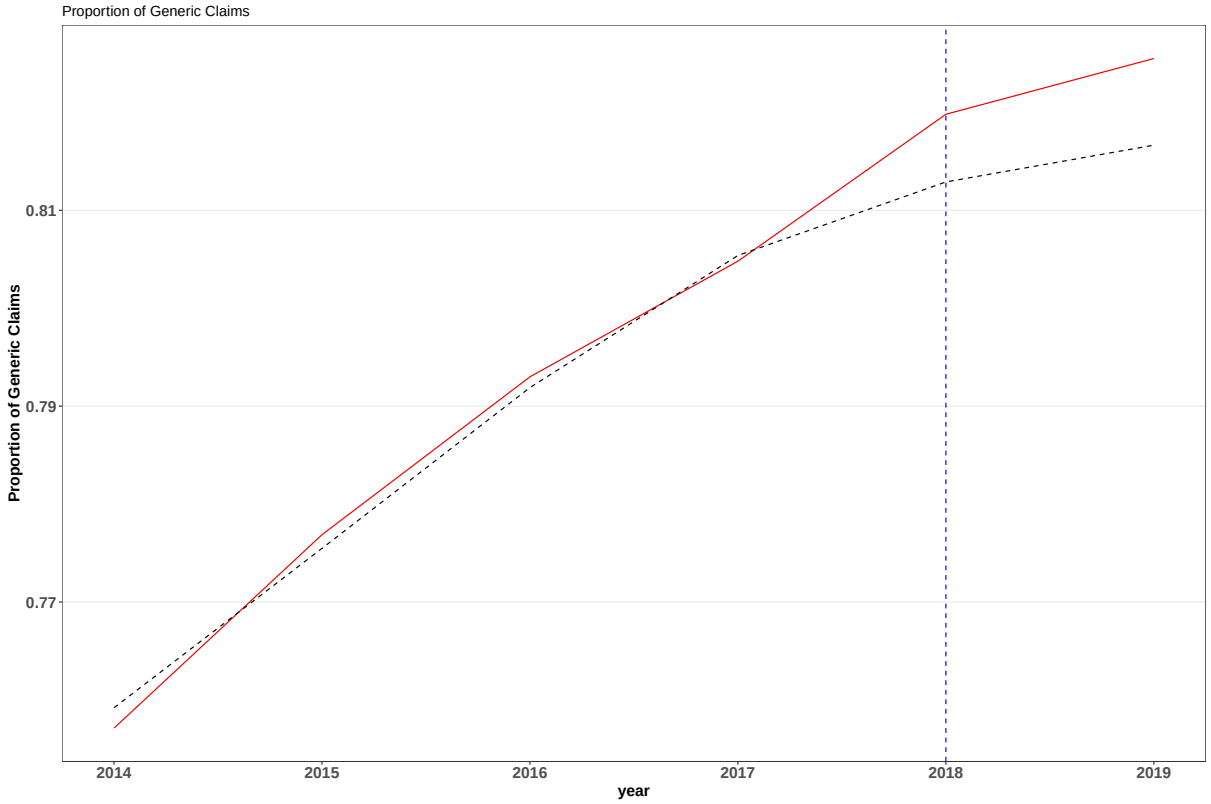
## 3.2 Synthetic Control: Reduced Form Results

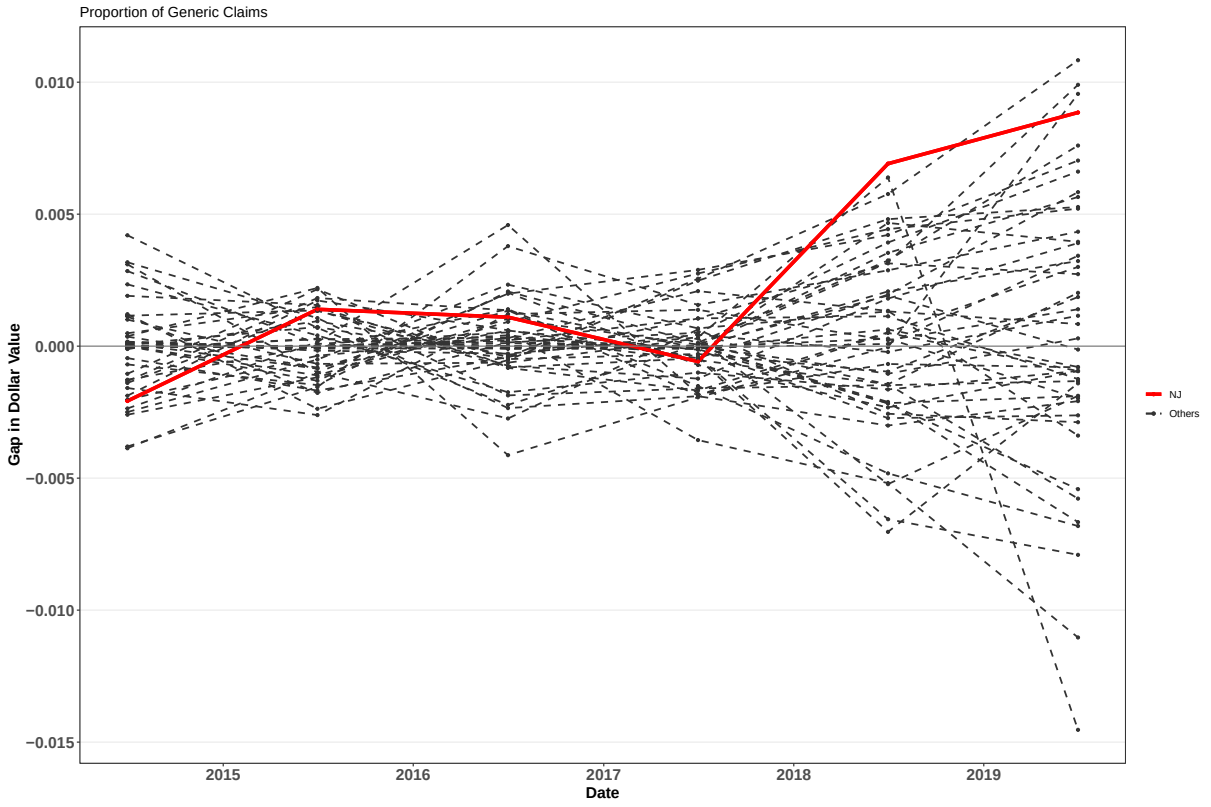


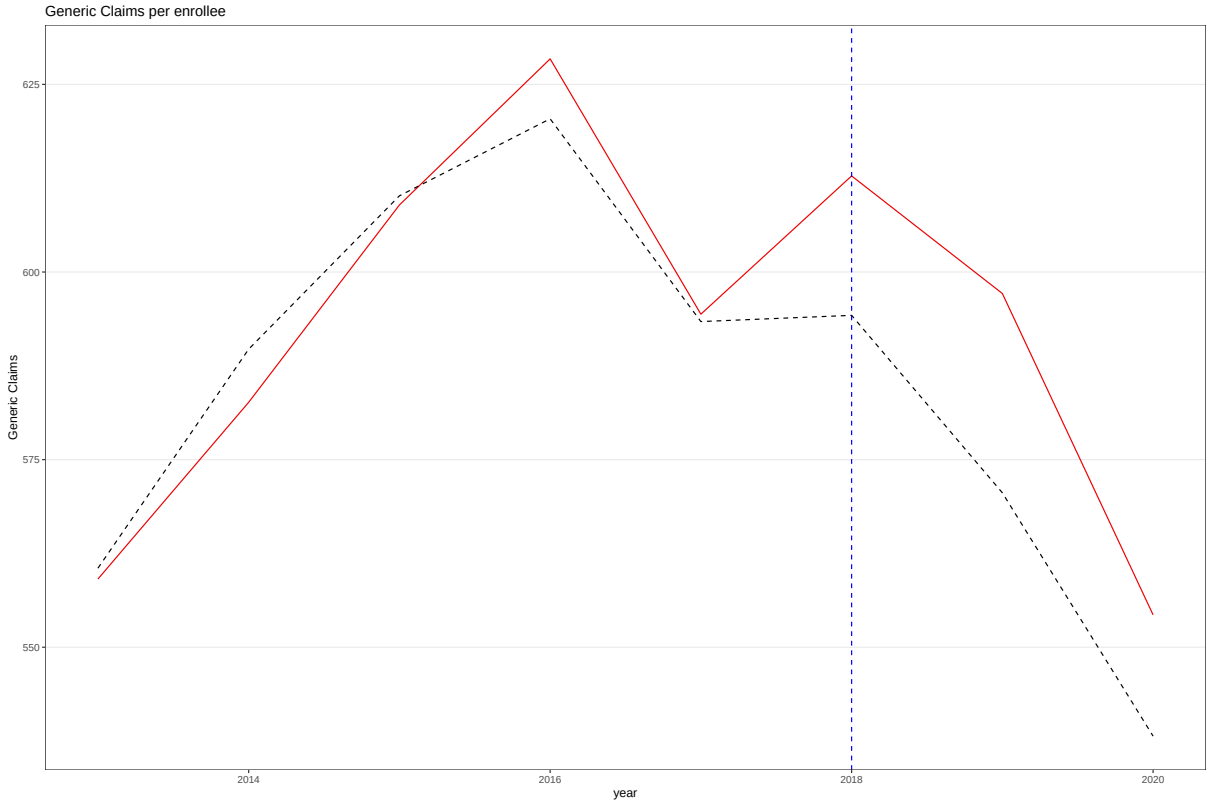

Brand Claims per enrollee (placebo)
Gap in Brand Claims
0.4
0.2
0.0
−0.2
2015
2016
2017
2018
2019
Date
NJ
Others

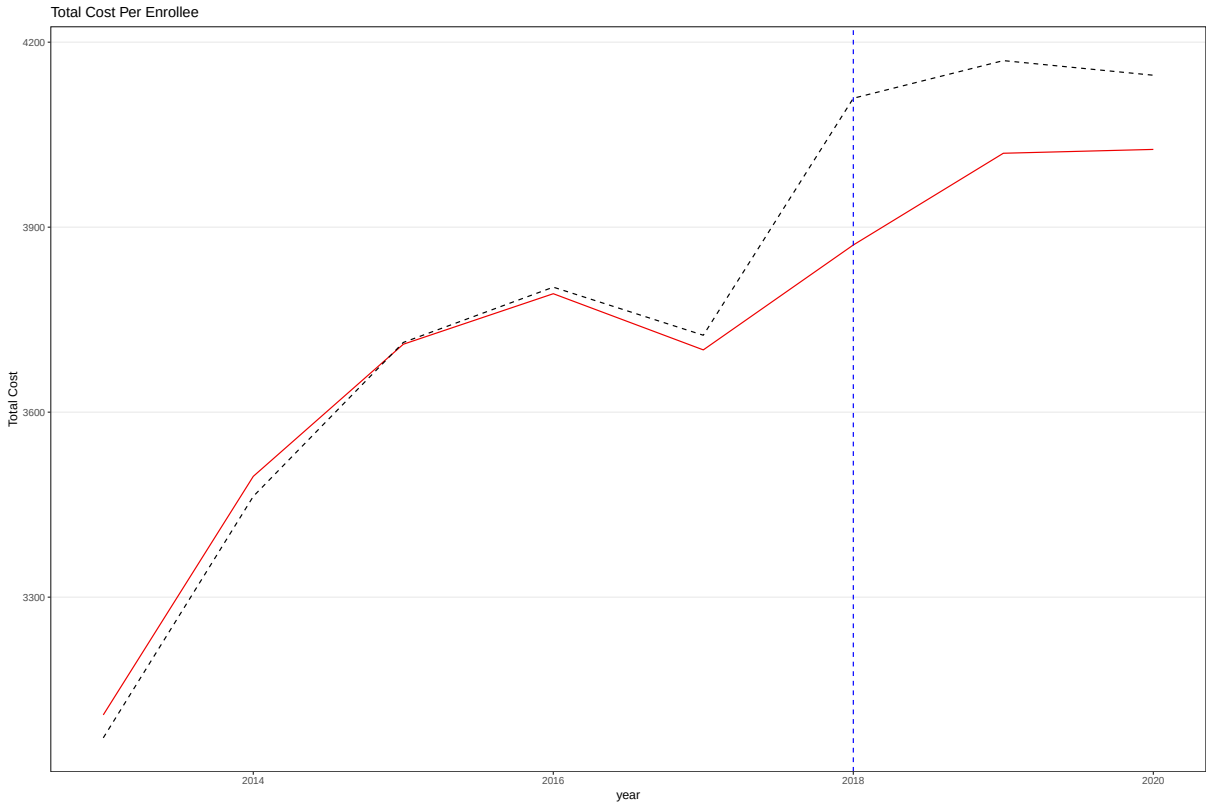

Proportion of Brand Claims
Brand Claim Prportion
0.23
0.21
0.19
2014
2015
2016
2017
2018
2019
year

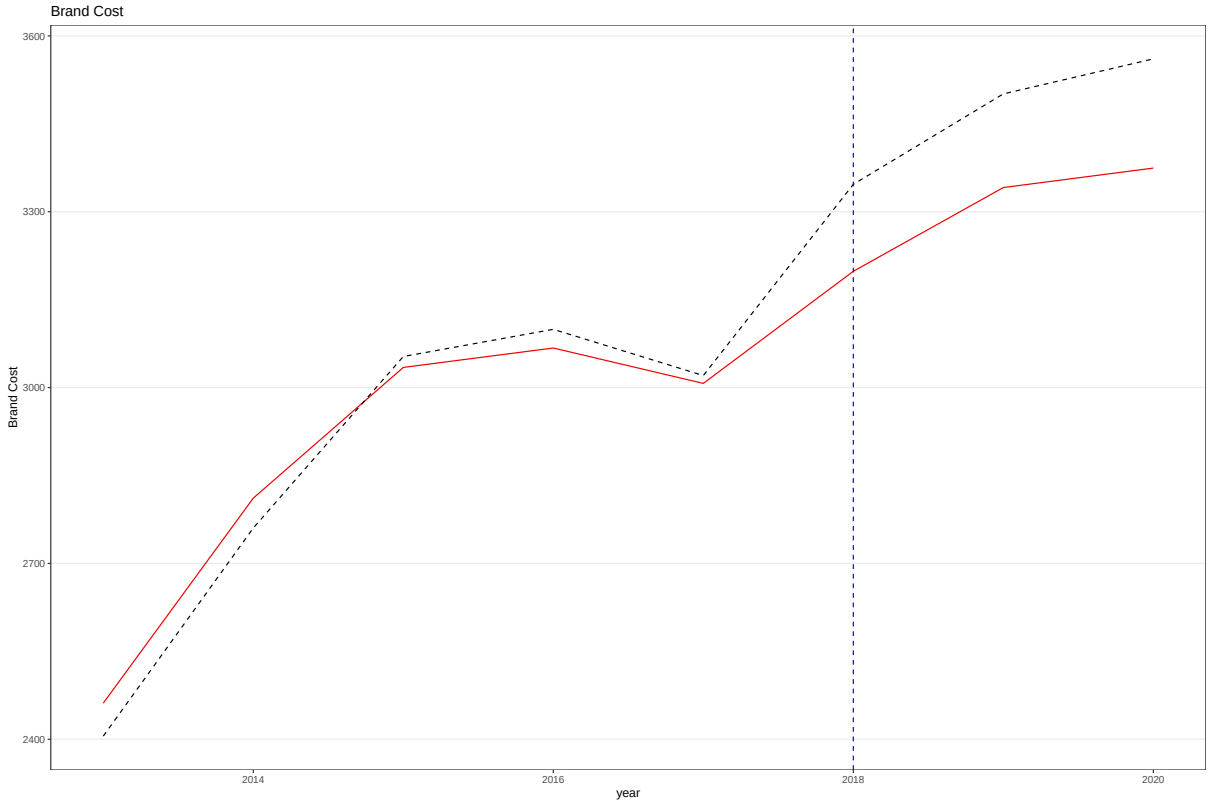

Proportion of Brand Claims
Gap in Dollar Value
0.015
0.010
0.005
0.000
−0.005
−0.010
2015
2016
2017
2018
2019
Date
NJ
Others


Proportion of Generic Claims
Proportion of Generic Claims
0.81
0.79
0.77
2014
2015
2016
2017
2018
2019
year


Proportion of Generic Claims
Gap in Dollar Value
0.010
0.005
0.000
−0.005
−0.010
−0.015
2015
2016
2017
2018
2019
Date
NJ
Others


Generic Claims per enrollee
625
600
575
550
Generic Claims
2014
2016
2018
2020
year


Total Cost Per Enrollee
4200
3900
3600
3300
Total Cost
2014
2016
2018
2020
year


Brand Cost
3600
3300
3000
2700
2400
Brand Cost
2014
2016
2018
2020
year

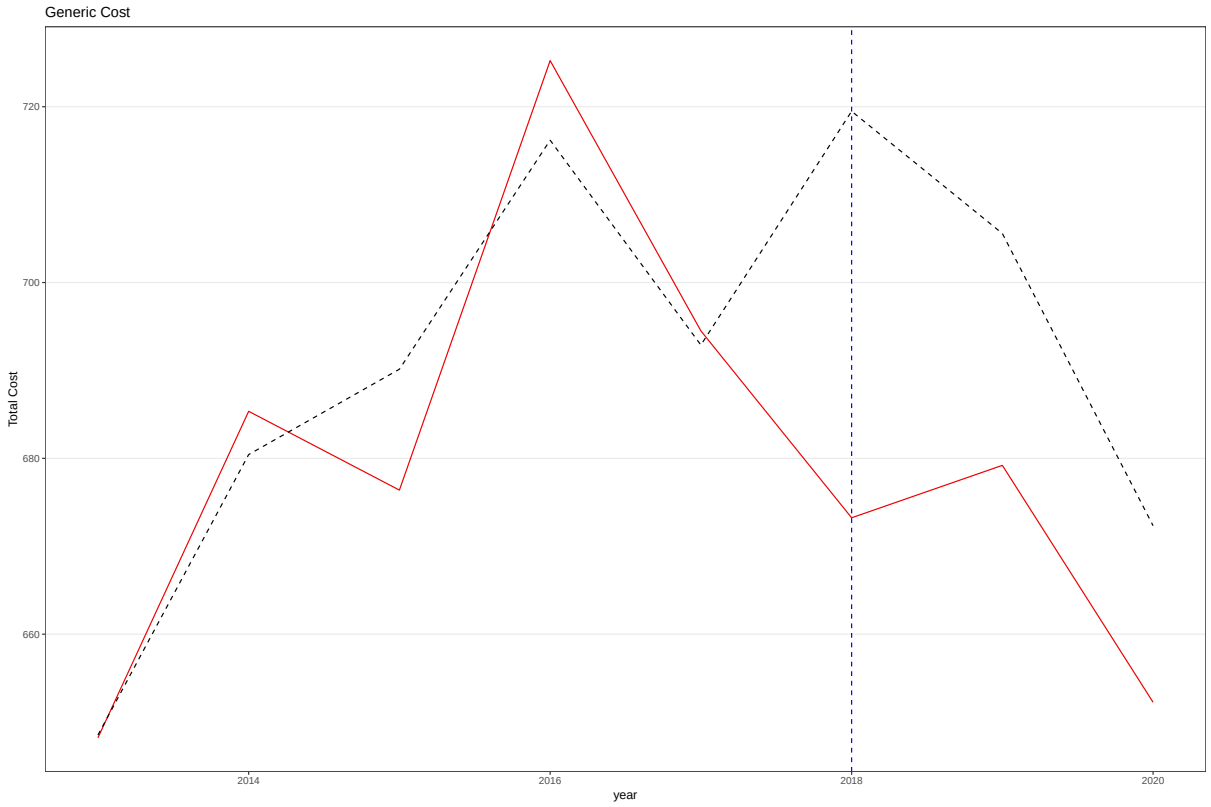

Generic Cost
720
700
680
660
Total Cost
2014
2016
2018
2020
year

Table 3: Effect of Policy on Prescription Patterns and Costs

| | Estimate | P-Value | Sample Mean | NJ Rank |
|---|---|---|---|---|
| *Number of Claims Per Part D Enrollee* | | | | |
| Total Claim | 0.02 | 0.549 | 29.79 | 28/51 |
| Brand Claim | -0.14 | 0.216 | 6.47 | 11/51 |
| Generic Claim | 0.64 | 0.902 | 22.21 | 46/51 |
| *Drug Cost Per Part D Enrollee* | | | | |
| Total Cost | -175.99 | 0.157 | 3561.67 | 8/51 |
| Brand Cost | -173.51 | 0.118 | 2867.38 | 6/51 |
| Generic Cost | -31.21 | 0.157 | 685.94 | 8/51 |
| *Proportions Brand or Generic* | | | | |
| Share of Brand Claims | -0.01 | 0.039 | 0.22 | 2/51 |
| Share of Generic Claims | 0.01 | 0.9 | 0.78 | 46/51 |
| Share of Brand Cost | -0.0005 | 0.585 | 0.77 | 30/51 |
| Share of Generic Cost | 0.0005 | 0.431 | 0.23 | 22/51 |

# 4 Robustness (TBC)

## 4.1 Sample Construction

## 4.2 Results without matching

## 4.3 Using all states as controls

# 5 Details about the Regulations (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. California and Nevada require pharmaceutical firms to comply with the Pharmaceutical Research and Manufacturers of America (PhRMA) code of conduct. New Jersey law is the first of its kind and is unique in several aspects.1 First, since its implementation is long after the passage of the PPSA, it allows the utilization of the resulting rich transfer data to analyze the path 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 rich and stringent set of regulations on almost all categories of payments, from capping small payments for lunch and dinners to larger payments for bonafide services. The bona-fide services are those provided by a prescriber pursuant to an arrangement formalized in a written agreement, including presentations as speakers at promotional activities and education events, participation on advisory boards, and consulting arrangements. 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. 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 salespeople, 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. 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.

2. Any financial benefit or benefit in kind, any entertainment or recreational items.

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

4. The aggregate value of payments for bona fide services should not exceed $10,000 in aggregate in any calendar year from all pharmaceutical manufacturers. Payments for speaking at educational 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. The rule applies to physicians with an active NJ license who either practice in NJ or have NJ patients. This implies that the policy does not affect doctors without NJ licenses who practice in NY and PA close to NJ borders. The law does not provide for penalties against pharmaceutical manufacturers for violations. Instead, enforcement will rest with the prescribers' respective licensing boards, with the authority to impose disciplinary action and/or civil penalties. This

is unprecedented and contrary to all other laws that penalize pharmaceutical firms.

# 6 Details about Open Payment

Table 4: Frequency and Value of Payments by Nature (2014-2020)

| | %(Frequency) | %(Value) |
|---|---|---|
| **Food and Beverage** | 90.58 | 13.80 |
| **Travel and Lodging** | 3.57 | 7.87 |
| **Compensation for services other than consulting** | 2.22 | 32.41 |
| Education | 2.22 | 1.61 |
| **Consulting Fee** | 0.73 | 13.72 |
| Gift | 0.23 | 0.74 |
| **Honoraria** | 0.16 | 2.34 |
| Compensation for serving as faculty or speaker (non-accredited) | 0.07 | 1.11 |
| Royalty or License | 0.05 | 23.18 |
| Space rental or facility fees | 0.06 | 0.88 |
| Entertainment | 0.02 | 0.03 |
| Grant | 0.06 | 1.40 |
| Compensation for serving as faculty or speaker (accredited) | 0.01 | 0.17 |
| Charitable Contribution | 0.003 | 0.23 |
| Current or prospective ownership | 0.02 | 0.54 |
| $N$ | 53,173,081 | 7.1 Billion |

* Definition for each category is provided in figure 1

Figure 6: Definitions for Each Category of Payment

| Nature of payment | Definition |
|---|---|
| Consulting fee | Payments made to physicians for advice and expertise on a particular medical product or treatment, typically provided under a written agreement and in response to a particular business need. These payments often vary depending on the experience of the physician being consulted. |
| Compensation for services other than consulting, including serving as faculty or as a speaker at an event other than a continuing education program. | Payments made to physicians for speaking, training, and education engagements that are not for continuing education |
| Honoraria | Similar to consulting fees, but generally reserved for a one-time, short duration activity. Also distinguishable in that they are generally provided for services which custom prohibits a price from being set. |
| Gift | A general category, which will often include anything provided to a physician or teaching hospital that does not fit into another category |
| Entertainment | Attendance at recreational, cultural, sporting or other events that would generally have a cost |
| Food and beverage | Food and beverage |
| Travel and lodging | Travel and lodging |
| Education | This category generally includes payments or transfers of value for classes, activities, programs or events that involve the imparting or acquiring of particular knowledge or skills, such as those used for a profession. This category can include things like textbooks and medical journal articles. |
| Research | Payment for different types of research activities, including enrolling patients into studies of new drugs or devices. |
| Charitable contribution | Any payment or transfer of value made to an organization with tax-exempt status under the Internal Revenue Code of 1986, but only if it is not more specifically described by one of the other nature or payment categories. |
| Royalty or license | Royalty or other payment based on sales of products that use a physician's intellectual property. |
| Current or prospective ownership or investment interest | Ownership or investment interests currently held by physicians and teaching hospitals, as well as ownership interests or investments that physicians and teaching hospitals have not yet exercised |
| Compensation for serving as faculty or as a speaker for an unaccredited and non-certified continuing education program | Compensation for serving as faculty or as a speaker for an unaccredited and non-certified continuing education program |
| Compensation for serving as faculty or as a speaker for an accredited or certified continuing education program | Compensation for serving as faculty or as a speaker for an accredited or certified continuing education program |
| Grant | Payments to a physician or teaching hospital in support of a specific cause or activity. |
| Space rental or facility fees | Fees for renting space or facilities, in a teaching hospital, for example. |

# References

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505.

Bohn, S., Lofstrom, M., and Raphael, S. (2014). Did the 2007 legal arizona workers act reduce the state's unauthorized immigrant population? *Review of Economics and Statistics*, 96(2):258–269.

Hansen, B. B. (2004). Full matching in an observational study of coaching for the sat. *Journal of the American Statistical Association*, 99(467):609–618.

Hansen, B. B. and Klopfer, S. O. (2006). Optimal full matching and related designs via network flows. *Journal of computational and Graphical Statistics*, 15(3):609–627.

Stuart, E. A., King, G., Imai, K., and Ho, D. (2011). Matchit: nonparametric preprocessing for parametric causal inference. *Journal of statistical software*.