ESSAYS ON PATIENT HEALTH INSURANCE CHOICE AND PHYSICIAN PRESCRIBING BEHAVIOR

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Svetlana N. Beilfuss

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THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF DISSERTATION APPROVAL

Dr. Jillian Carr, Co-Chair

Department of Economics

Dr. Victoria Prowse, Co-Chair

Department of Economics

Dr. Timothy Moore

Department of Economics

Dr. Kevin Mumford

Department of Economics

Dr. Brigitte Waldorf

Department of Agricultural Economics

Approved by:

Dr. Brian Roberson

Director of Graduate Studies in Economics

For Koli.

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ABSTRACT

Beilfuss, Svetlana N. Ph.D., Purdue University, August 2020. Essays on Patient Health Insurance Choice and Physician Prescribing Behavior. Major Professors: Victoria Prowse, Jillian Carr.

This dissertation consists of three chapters. The first chapter, "Inertia and Switching in Health Insurance Plans," seeks to examine health insurance choice of families and individuals employed by a large Midwestern public university during the years 2012-2016. A growing number of studies indicate that consumers do not understand the basics of health insurance, make inefficient plan choices, and may hesitate to switch plans even when it is optimal to do so. In this study, I identify what are later defined as unanticipated, exogenous health shocks in the health insurance claims data, in order to examine their effect on families' plan choice and switching behavior. Observing switches into relatively generous plans after a shock is indicative of adverse selection. Adverse retention and inertia, on the other hand, may be present if people remain in the relatively less generous plans after experiencing a shock. The results could help inform the policy-makers about consumer cost-effectiveness in plan choice over time.

Physicians' relationships with the pharmaceutical industry have recently come under public scrutiny, particularly in the context of opioid drug prescribing. The second chapter, "Pharmaceutical Opioid Marketing and Physician Prescribing Behavior," examines the effect of doctor-industry marketing interactions on subsequent prescribing patterns of opioids using linked Medicare Part D and Open Payments data for the years 2014-2017. Results indicate that both the number and the dollar value of marketing visits increase physicians' patented opioid claims. Furthermore, direct-to-physician marketing of safer abuse-deterrent formulations of opioids is the primary driver of positive and persistent spillovers on the prescribing of less safe generic opioids - a result that may be driven by insurance coverage policies. These findings suggest that pharmaceutical marketing efforts may have unintended public health implications.

The third chapter, "Accountable Care Organizations and Physician Antibiotic Prescribing Behavior," examines the effects of Accountable Care Organizations (ACOs). Physician accountable care organization affiliation has been found to reduce cost and improve quality across metrics that are directly measured by the ACO shared savings program. However, little is known about potential spillover effects from this program onto non-measured physician behavior such as antibiotic over-prescribing. Using a two-part structural selection model that accounts for selection into treatment (ACO group), and non-treatment (control group), this chapter compares physician/nurse antibiotic prescribing across these groups with adjustment for geographic, physician, patient and institutional characteristics. Heterogeneous treatment responses across specialties are also estimated. The findings indicate that ACO affiliation helps reduce antibiotic prescribing by 23.9 prescriptions (about 19.4 percent) per year. The treatment effects are found to vary with specialty with internal medicine physicians experiencing an average decrease of 19 percent, family and general practice physicians a decrease of 16 percent, and nurse practitioners a reduction of 12.5 percent in their antibiotic prescribing per year. In terms of selection into treatment, the failure to account for selection on physician unobservable characteristics results in an understating of the average treatment effects. In assessing the impact of programs, such as the ACO Shared Savings Program, which act to augment how physicians interact with each other and their patients, it is important to account for spillover effects. As an example of such spillover effect - this study finds that ACO affiliation has had a measurable impact on physician antibiotic prescribing.

1. INERTIA AND SWITCHING IN HEALTH INSURANCE PLANS

1.1 Introduction

Healthcare spending in the United States has grown rapidly over the last half of a century, taking up a larger and larger proportion of the gross domestic product (GDP). The introduction of high-deductible health insurance plans (HDHPs) combined with a health savings account (HSA) is seen as one way to limit medical spending growth. HSA health insurance accounts create incentives for the covered individuals to reduce the consumption of medical services leading to a reduction in medical costs (Peter et al., 2016). In addition to the medical cost problem, a growing body of literature is finding that consumers are making inefficient (not cost-minimizing) plan choices due to difficulties with understanding and sorting through the large and complex menu of health insurance choice options, often leading to overspending on medical care. The initially-inefficient plan choice may be further aggravated by what's known as inertia in plan choice where people tend to remain in the same plan year after year even when better options are available. In many cases, an alternative plan would be a better fit, reducing the amount that a family spends on healthcare. For example, Handel (2013) Handel finds that employees at a large firm overspend by about $2,032 per year due to inertia. To decrease inertia, consumers must be willing to switch into other available plans. However, literature on plan switching indicates that plan complexity can inhibit consumer switching and produce results that go against standard model predictions (Elbel and Schlesinger, 2006; Frank and Lamiraud, 2009). Loss aversion, where consumers see the disadvantages from switching as outweighing the advantages of new options, can also contribute to low rates of plan switching. In addition to health insurance studies, a number of Medicare Part D studies find that reducing inertia could have a substantial effect on increasing consumer welfare (Ericson, 2014; Ho et al., 2015; Polyakova, 2016).

A growing number of studies indicate that consumers do not understand the basics of health insurance (Bhargava et al., 2017). For example, Sinaiko and Hirth (2011) find that a large proportion of University of Michigan employees enrolled in (non-financially) dominated plans, choosing to forgo options with better specialist referrals and out-of-network care. Studies examining choices of prescription drug plans in Medicare Part D have found that a larger number of elderly enrollees chose plans that are not cost-minimizing. Much of the inefficiency is estimated to be driven by plan choice inertia, and whether such choices improve over time through switching is unclear (Abaluck and Gruber, 2011, 2016; Heiss et al., 2010; Ketcham et al., 2012).

Cutler et al. (2010) identified two factors that play a role in people's staying/switching behavior - adverse selection and adverse retention. Adverse selection is the movement of the less healthy individuals into more generous plans. For example, a person who contracted a serious illness and expects to be sick in the future may select (or switch) into a more generous plan. On the other hand, adverse retention is defined as a tendency for people to stay in the plan they are in when they get sick. This may happen due to existence of switching costs (whether tangible or psychological), which traditional models of plan choice assume away. For example, individuals who are in the process of receiving treatment may be reluctant to switch care midstream. In addition, consumers may be reluctant to incur hassle costs associated with switching plans, such as transferring medical records, finding new doctors and getting new medical tests. It may also be the case that they believe their doctor is better than average, and may not want to switch plans even if they know that other plans are more efficient. Samuelson and Zeckhauser (1988) find that individuals are reluctant to switch health plans or change any of the established choices in general.

This paper seeks to examine health insurance choice of families and individuals employed by a large Midwestern public university during the years 2012-2016, and identify potential signs of adverse selection, retention, and/or inertia. I identify what are later defined as unanticipated, exogenous health shocks in the health insurance claims data, in order to examine their effect on families' plan choice and switching behavior. Observing switches into relatively generous plans after a shock is indicative of adverse selection. Adverse retention and inertia, on the other hand, may be present if people remain in the

relatively less generous plans after experiencing a shock. The results could help inform about consumer cost-effectiveness in plan choice over time.

1.2 Institutional Background

Prior to 2014, the university offered three types of health insurance plans to its employees - a high-deductible plan with an HSA account and two non-HSA plans with lower cost-sharing. In 2014, these plans were replaced by three new health insurance plans, including two high-deductible plans with HSA. Compared to old plans, the new plans had lower premiums and higher cost-sharing structures. The stated reasons for the switch included adjustments to meet the requirements of the Affordable Care Act and to encourage employees to be better health consumers in order to help reduce expenses to the medical plans in general. In addition, more HSA options allow policyholders to accumulate balances and pay for qualified health care services without federal tax liability. Such tax advantages make high-deductible plans an attractive alternative to more generous (or, low cost-sharing) health plans, whose premiums are typically higher. However, critics of HSAs argue that older, higher-income households derive the greatest benefit from such tax advantages and may attract disproportionately many healthy individuals. The literature suggests that high-income households are considerably more likely than low-income households to contribute to HSAs, even though disease prevalence is inversely associated with income (Helmchen et al., 2015). Furthermore, Fronstin et al. (2013) find that HSAs are associated with reduced medication adherence for chronic conditions, which can adversely impact productivity and medical costs.

Specifically in the context of the university's policy, an employee can elect to set aside dollars on a pre-tax basis through payroll deductions that would go directly into an HSA account. The individual can then make contributions to their HSA account as long as the total combined contributions from both the employee and the university do not exceed $6,650 (when covering one or more family members)[1]. The funds in the HSA are invested in an interest-bearing savings account, and when the account balance reaches

[1]If the employee is 55 years old or older, they can contribute an additional $1,000 per year.

$1,000, additional investment options (such as money market fund) become available. Any earnings on those investments are tax-free if used to pay for eligible health care expenses.

1.3 Data and Empirical Specification

This study utilizes health insurance claims data on the university employees[2] and their dependents for years 2012-2016, focusing on the new plan period 2014-2016. The data comes from a file that contains de-identified eligibility, medical, and prescription records, processed by both Truven Health Analytics and the university. The following three equations are estimated using system GMM (Generalized Method of Moments). The dynamic panel approach accounts for heteroscedasticity and correlation within the family, as well as the family fixed effects (which control for family's overall health).

$$HEALTH_{i,t} = \beta_0 + \beta_1 shock_{i,t-1} + \beta_2 year2015_{i,t-1} + \beta_3 HEALTH_{i,t-1} + \beta_4 HEALTH * shock_{i,t-1} + \beta_5 HSA2_{i,t-1} + \beta_6 HSA2 * shock_{i,t-1} + \beta_7 X_{i,t-1} + u_{i,t} \tag{1.1}$$

$$HSA1_{i,t} = \alpha_0 + \alpha_1 shock_{i,t-1} + \alpha_2 year2015_{i,t-1} + \alpha_3 HSA1_{i,t-1} + \alpha_4 HSA1 * shock_{i,t-1} + \alpha_5 HSA2_{i,t-1} + \alpha_6 HSA2 * shock_{i,t-1} + \alpha_7 X_{i,t-1} + e_{i,t} \tag{1.2}$$

$$HSA2_{i,t} = \delta_0 + \delta_1 shock_{i,t-1} + \delta_2 year2015_{i,t-1} + \delta_3 HSA2_{i,t-1} + \delta_4 HSA2 * shock_{i,t-1} + \delta_5 HEALTH_{i,t-1} + \delta_6 HEALTH * shock_{i,t-1} + \delta_7 X_{i,t-1} + v_{i,t} \tag{1.3}$$

The unit of observation is family i in year t during the 2014-2016 time period. The family is defined such that it may consist of one person (single coverage) or multiple individuals (employee and spouse coverage, employee and children coverage, or family coverage). While I examine families in the new plans, namely for years 2014-2016, I restrict the sample to include only families that have been covered by the university insurance for the entire 2012-2016 time-frame. Additionally, each member within the family will necessarily have continuous coverage for the entire time period of 2012-2016.

[2]Excluding graduate students, who are covered by the entirely different plans, not discussed here.

The dependent variable in each equation is a binary indicator equal to 1 if family i is observed to be enrolled in one of the three plans (*HEALTH, HSA1, or HSA2*) in year t. The three plans include the lowest cost-sharing and most expensive plan without HSA, *HEALTH*, the medium cost-sharing and medium-priced plan with HSA, *HSA1*, and the highest cost-sharing and least expensive plan with HSA, *HSA2*. Thus, the Health plan is the most generous plan. This low-deductible, high-premium plan is designed for people with relatively high medical expenses. HSA1 and HSA2 are middle- and low-generosity plans, respectively, with lower premiums but higher cost-sharing structures.[3]

The explanatory variables of interest are the lagged exogenous health shocks and plan-shock interactions. A family i that experienced a health shock in the prior calendar year will have the indicator variable $shock_{i,t-1}$ equal 1. The plan-shock interactions are included in order to account for differential plan effects of the shocks. For example, a family that experienced a health shock while enrolled in the Health plan in *t-1* may have a different probability of enrolling in the Health plan in year t, compared to a family that had a shock while enrolled in the HSA2 plan in the prior year. I define exogenous health shocks as having a diagnosis code for at least one of the following: cancer (excluding leukemia), acute asthma, chronic kidney disease (stage one, two, three, four, five, end-stage renal disease, or unspecified chronic kidney disease), type 1 diabetes, premature birth (up to thirty-two weeks of gestation), birth trauma, traumatic brain injury (intracranial injury), heart attack, heart failure, or stroke.[4] If any of these shocks are observed within the family i in year t, and no other shocks were observed in the family i prior to year t, then $shock_{i,t} = 1$. It then follows that a family is allowed to only have one shock-year during the entire 2012-2016 period,[5] although I analyze their reaction to the shock for years 2014-2016.

While this methodology does not exclude the possibility that the family was aware of the health condition prior to the shocks's appearance in the dataset, observing the family for two years in the old plan environment (2012-2013) should lessen the concern that the

[3]See Table A.4 for plan information and comparisons.

[4]Tables A.2 and A.3 in Appendix A contain information on the number of families experiencing shocks and their distribution across plans, as well as the number and type of shocks for years 2014 and 2015.

[5]Note that while a family can only have one year to experience a shock, more than one new shock can be experienced by that family during that year. This way, a family is allowed to "react" to the shock(s)-year by switching plans (or staying in the same plan) in the following year.

conditions classified as shocks during time-frame of the main analysis (2014-2016) existed prior to this time-frame. Even if the family was aware of the condition leading to the shock prior to its appearance in the dataset, I would expect such family to be in the most appropriate plan for the condition and less likely to switch out of it. This would bias my estimates toward not finding an effect of the health shock on plan switching.

In addition to the dummy variable for year 2015, the control variables (vector X) include an indicator for whether the primary policyholder is salaried (as opposed to part-time), policyholder's age in years, the number of dependent children 18 years of age or younger covered by the plan, an indicator for presence of a spouse covered by the plan, the number of family claims, and the family out-of-pocket prescription spending in dollars.[6] The overall family health is controlled for by the fixed effects of the system GMM estimator.

1.4 Results

Table A.5 presents the estimation results. The first column contains coefficient estimates for equation (1.1). The estimate on the lagged Health plan is suggestive of inertia. A family without any health shocks that was enrolled in the Health plan during the prior year is 63 percentage points more likely to re-enroll in this generous plan compared to a similar family who was enrolled in the HSA1 plan (the omitted category) during the previous year. However, if in the prior year the family experienced an exogenous health shock while being enrolled in the Health plan, this decreases the chances that the family will pick it again, as suggested by the negative and significant coefficient estimate on the interaction term $HEALTH * shock$. Specifically, a family that experienced a shock while in the most generous plan is now 49.5 percentage points (-0.137+0.632) more likely to enroll in the Health plan compared to a similar family who was enrolled in HSA1 during the prior year - the probability of re-enrollment is now lower. The fact that experiencing a serious health shock lowers the probability of enrolling in this generous plan is surprising, considering the high long-term costs associated with a serious illness. The coefficient estimates for families with health shocks enrolled in both HSA1 and HSA2 during the prior

[6]See Table A.1 in Appendix A for the summary statistics

year (0.0355 and 0.003, respectively) are positive, suggesting that people may respond to *t-1* shocks by enrolling in the Health plan in year t. Unfortunately, these estimates are not significant as a result of imprecision. The coefficient estimate on families' past year's claims is significant at a 10%-level (although small in magnitude), suggesting that a family with more claims in the past is more likely to enroll in the Health plan.

The second column of Table A.5 contains the coefficient estimates for equation (1.2). The coefficient estimates on $HSA1_{t-1}$ and $HSA1 * shock_{t-1}$ suggest a high level of inertia for families without shocks - people are 70.5 percentage points more likely to enroll in HSA1 if they were in HSA1 in the previous year compared to families who were in the Health plan before. Experiencing a shock while in HSA1 decreases the probability that they will again enroll in HSA1 by about 14 percentage points - a shocked family coming from HSA1 is now only 56.6 percentage points more likely to enroll in HSA1 compared to a shocked family that came from the Health plan. The positive and significant coefficient on $shock_{t-1}$ suggests that families who had a health shock while in the Health plan are about 8.6 percentage points more likely to enroll in HSA1 relative to similar families without shocks from the Health plan. This result is consistent with the estimates for specification (1.1), suggesting that people who got shocks while in the Health plan are likely switching to a different plan. Additionally, the negative and significant coefficient on $HSA2 * shock_{t-1}$ suggests that families who had a shock while in the "cheapest" plan (HSA2), are 36 percentage points less likely to enroll in HSA1 the following year compared to families who had a shock while in the most generous plan (Health). Furthermore, having a shock while in the cheapest plan (HSA2) decreases the probability of enrolling in the middle generosity plan (HSA1) by 25 percentage points (-0.363+0.0855) compared to not having a shock. Both results appear to suggest that shocks make it less likely to upgrade from HSA2 to HSA1. For the control variables, the estimates suggest that each additional child under 19 years of age increases the probability of enrolling in the middle generosity plan by 38 percentage points. A family with the main policyholder who is salaried and *t-1* being 2015 both decrease the probability of choosing HSA1, while main plan-holder's age has a positive effect on the probability of picking HSA1.

The third column of Table A.5 contains the estimation results for equation (1.3). The coefficient estimate on $HSA2_{t-1}$ suggests that a no-shock family is 53 percentage

points more likely to enroll in HSA2 again compared to a similar family from HSA1. Experiencing a shock appears to strengthen this effect, with 74 percentage point increase in probability of re-enrolling in this plan after a shock compared to a similar family coming from HSA1. This result is surprising, since one would expect that a family in the this cheapest plan would certainly switch into a more generous plan once a serious health shock is experienced. While indicative of adverse retention, the fact that this plan is, in some cases, free (in addition to HSA2 being the automatic default plan), may play a role in explaining why the families may be hesitant to switch out of it, even in the case of a serious illness.

1.5 Discussion

The results for all three specifications suggest a strong presence of inertia across all three health insurance plans for families without shocks, after controlling for health status and other characteristics. Families were 63 percentage points more likely to re-enroll in the most expensive plan, 71 percentage points more likely to re-enroll in the middle generosity plan, and 53 percentage points more likely to re-enroll in the least generous plan when no shocks were observed.[7] Without further cost analysis, it is difficult to determine how many people are enrolled in these plans in an optimal way, and thus approximate the level of inertia. However, its likely presence may be potentially problematic, since it may indicate people's inability and/or unwillingness to change plans that could result in overspending if the initial plan choice is not cost-minimizing.

Additionally, the results suggest that in all but the cheapest plan, serious health shocks may induce people out of inertia-type behavior. For example, given the family was enrolled in the most generous plan in the prior year, experiencing a shock reduces the probability of re-enrollment by roughly 10 percentage points ($\beta_1 + \beta_4$). Assuming that the most generous plan is more suitable for higher-cost illnesses, this result is somewhat surprising. Experiencing a shock in the middle-generosity plan (HSA1) reduces the chance of HSA1 re-enrollment by 5.4 percentage points ($\alpha_1 + \alpha_4$), with most switchers upgrading to Health and some downgrading to HSA2. Switching out of HSA1 and into Health may

[7]Relative to the respective omitted plan type.

stem from the desire for more generous coverage after a shock, and may point toward existence of adverse selection. On the other hand, switching into a less generous plan after a serious shock is puzzling and requires further evaluation.

Possible presence of adverse retention is indicated by the fact that employees in the cheapest and least generous plan (HSA2) are 22 percentage points more likely to re-enroll in the plan after experiencing an unanticipated health shock, relative to not having one. Thus, health shocks appear to reinforce the inertia already observed in the HSA2 plan. Part of the explanation for the initial inertia (without shocks) in HSA2 may lie in the university's default policy. In 2014, the university started defaulting existing employees (and their families) into HSA2 without university HSA contribution[8]. In the following years, employees who did not make an active plan choice would be defaulted into their prior year's coverage. On the other hand, shock-induced inertia in HSA2 may have several explanations. One reason people may not want to switch into a more generous coverage may stem from the adverse retention argument, where people are unwilling to incur plan switching costs. Another explanation for families' unwillingness to switch even when it may be beneficial is due to HSA2's very low price compared to other plans (in the case of single coverage, it is free).[9] Additionally, the advantage of going to an HSA plan include tax-free savings that can later be used for qualifying health expenses and the university's annual contribution to the employee's HSA account, which may explain why people are switching from the more generous coverage to one of the HSA plans. In the case of shocks inducing HSA2 re-enrollment, the family may weigh the cost of their unanticipated health condition against the money they are saving from paying a low/zero premium in HSA2 and extra savings from the university contribution. Further cost-analysis is needed to interpret the results, and to approximate the extent of adverse retention and inertia.

1.6 Conclusion

The aim of the study is to examine family plan choice and the effect of unanticipated serious health shocks on families' switching/staying behavior. The results indicate possible presence adverse selection as well as inertia in plan choice, which may be further

[8]Prior to 2014, employees were defaulted into no coverage
[9]See Table A.4 for plan premiums.

aggravated by adverse retention. This points to the possibility that families are inefficient in choosing insurance plans which may lead them to overspend on healthcare. Unanticipated health shocks do not simply cause people to switch into more generous coverage, as would be consistent with the adverse selection argument. The shocks appear to draw individuals and families out of inertia and into both more and less generous plans. It may be the case that once people experience an unexpected illness, they pay more attention to the workings of the available healthcare plans, which could lead to improvement in plan choice. The important question is whether the switch is more or less cost-efficient for the employee and their family. Further investigation into the cost-efficiency of plan choices is necessary to examine whether families are learning about health insurance and becoming more efficient or if their behavior is consistent with less efficient choices.

2. PHARMACEUTICAL OPIOID MARKETING AND PHYSICIAN PRESCRIBING BEHAVIOR

2.1 Introduction

The abuse of prescription opioids and the resulting overdose deaths have reached unparalleled levels in the United States over the last few years. In 2016, 63,632 individuals died from drug overdoses, with 66.4% of the cases involving opioids. Among opioid-related deaths, 40.4% involved prescription opioids (Centers for Disease Control and Prevention, 2018). Furthermore, two million people in the United States suffer from opioid addiction due to prescription opioid drugs (Schuchat et al., 2017). Policymakers are attempting to combat the opioid epidemic through various approaches, especially focusing on limiting opioid prescriptions. For example, the Centers for Medicare and Medicaid Services (CMS) recently finalized a number of new policies to help Medicare plan sponsors combat prescription opioid overuse and misuse by imposing limits on initial opioid prescriptions fills and identifying high-risk opioid users. Additionally, some physicians and pharmaceutical industry representatives have encouraged the use of abuse-deterrent formulations (ADFs) – patented opioids with properties that make misuse more difficult – arguing that they provide a safer option for treatment of ongoing pain compared to the traditional formulations (Webster et al., 2017).

The abuse of prescription opioids and the resulting overdose deaths have reached unparalleled levels in the United States over the last few years. In 2016, 63,632 individuals died from drug overdoses, with 66.4% of the cases involving opioids. Among opioid-related deaths, 40.4% involved prescription opioids (Centers for Disease Control and Prevention, 2018). Furthermore, two million people in the United States suffer from opioid addiction due to prescription opioid drugs (Schuchat et al., 2017). Policymakers are attempting to combat the opioid epidemic through various approaches, especially focusing on limiting opioid prescriptions. For example, the Centers for Medicare and Medicaid Services (CMS) recently finalized a number of new policies to help Medicare plan sponsors combat pre-

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These changes are occurring at the same time as pharmaceuticals are being intensively marketed to doctors. In 2015, about 48% of physicians received industry-related payments (Tringale et al., 2017). Pharmaceutical companies spend more than $20,000 annually per physician on direct-to-physician advertising that may include gifts, samples, travel, consulting fees, and pharmaceutical detailing visits where company sales representatives educate a physician, usually over a meal, about their drugs in order to sway the physician to prescribe them (Weiss, 2010). In an effort to reduce pharmaceutical industry influence on prescribing, a large number of US hospitals and academic medical centers have imposed limits on interactions between physicians and pharmaceutical sales representatives. The question of how pharmaceutical marketing efforts aimed at physicians affect the consequent prescribing behavior has received considerable attention in the marketing literature and, to a smaller extent, in the economics literature (Datta and Dave, 2017). Studies looking at the link between direct-to-physician marketing and physician prescribing have uncovered mixed results in terms of the effectiveness of industry payments on increasing prescribing (Dave, 2013, 2014; Kremer et al., 2008). Some inconsistency in the results may be explained by the fact that the effects of the direct-to-physician promotion may be different depending on which pharmaceutical drugs are being examined and other data related differences.[1] However, the primary empirical concern is variation in how well the studies account for the targeting bias, where high-prescribing physicians are more likely to be targeted for marketing interactions by drug producers.

This study contributes to the literature of pharmaceutical promotion by quantifying the effect of doctor-industry interactions on subsequent prescribing patterns of opioids. Using longitudinal physician data from Medicare Part D and the Open Payments pro-

[1]See, for example, Berndt et al. (1995); Dave and Saffer (2012); Iizuka and Jin (2007); Rizzo (1999). For a comprehensive review of the pharmaceutical promotion literature, see Kremer et al. (2008) and Dave (2013, 2014).

gram for years 2014-2017, I examine how direct-to-physician marketing of patented opioid drugs affects physicians' patented and generic opioid claims. Because opioid-promoting companies target doctors who already prescribe large quantities of opioids (whether due to patient population characteristics or some unobserved doctor preferences), it is important to account for the high-prescriber selection into marketing relationships with opioid firms. I use physician fixed effects to control for the observed and unobserved doctor characteristics and prescribing preferences which may lead to such selection. Additionally, I include the interacted zip-code-by-year fixed effects in order to account for the unobserved geographical demand shocks that vary over time, which may affect both opioid promotion and prescribing behavior.

Results suggest that physician interactions with opioid companies indeed increase prescribing of patented opioid drugs. Specifically, detailing interactions with pharmaceutical sales representatives over meals drive the positive effect on patented prescribing, with higher-cost meals reinforcing the impact of promotional interactions on claims. My findings indicate that the average number of yearly promotional visits by pharmaceutical sales representatives causes physicians to increase their patented opioid prescribing by 13.3%. I also show that there exist unintended consequences of opioid promotion in the form of spillover effects on generic opioid prescribing. Instead of substituting away from relatively unsafe, misuse prone generic drugs, the average number of promotional interactions related to patented opioids induces physicians to increase generic prescribing by about 3.6%. Furthermore, the spillover effects on generic claims are persistent over the years and arise primarily from the marketing of abuse-deterrent opioids - the very drugs designed to prevent misuse. These spillover results are consistent with the pervasive insurance company policies that encourage generic prescribing and restrict patient access to costlier, but safer abuse-deterrent drugs.

In addition to the main empirical strategy, I employ an instrumental variable (IV) approach as a robustness check to show that my results hold under an alternative specification. I use the number of opioid marketing interactions and the value total industry payments for <u>other</u> doctors in the zip code as instruments for opioid-related interactions of a given doctor. This approach relies on the fact that a physician is more likely to have

an opioid marketing interaction if other local doctors are being frequented by opioid sales representatives.

Accounting for physician selection into marketing relationships with pharmaceutical firms is essential in order to accurately estimate the effect of direct-to-physician advertising on prescribing behavior. A number of studies utilize instrumental variable approaches, finding relatively smaller effects of marketing compared to studies that do not control for endogeneity (Azoulay, 2002; Kalyanaram, 2009; Rosenthal et al., 2003). Very few studies utilize the panel data framework, where physician fixed effects can be used to control for observed and unobserved physician heterogeneity in prescribing preferences that may also be correlated with targeted marketing activity. The exceptions are Datta and Dave (2017) and Mizik and Jacobson (2004) who use longitudinal data to look at the role of physician marketing on prescribing of various drugs.[2] Both studies find that the effect of direct-to-physician marketing is quite modest relative to studies not utilizing physician fixed effects, suggesting that selection bias plays a role in the observed relationship between promotion and drug sales.

One reason that some studies find little-to-no effect of advertising on sales is brand switching. One firm's promotional efforts reduce the rivals' sales, thereby causing the competing firms to increase their marketing activity (Bagwell, 2007). For example, in analyzing how pharmaceutical detailing affects prescribing of branded and generic drugs for treatment of Herpes infection, Datta and Dave (2017) find that while detailing does not crowd out cheaper generic prescriptions, class-level demand for branded drugs is only minimally affected. They find that physicians tend to substitute from prescribing one drug to prescribing a more expensive drug as the result of promotion.[3]

Recently, an enormous number of lawsuits have been brought against the opioid manufacturers in connection to the role that pharmaceutical promotion to physicians has played in the opioid epidemic. Importantly, while policy measures are being taken to reduce opioid prescribing, opioid manufacturers continue to pay doctors large sums of money to promote their products in an attempt to induce physicians to prescribe more

[2]Additionally, Dong et al. (2011, 2009) use full-information Bayesian methods in the framework of a physician-level panel data.

[3]Substitution between branded and generic drugs has not been well addressed in the literature. Only Janakiraman et al. (2008) include both on-patent and off-patent drugs, out of all physician-level longitudinal studies reviewed by Kremer et al. (2008).

opioid drugs. However, surprisingly little is known about the relationship between direct-to-physician promotional activities and opioid prescribing. To my knowledge, only three studies have looked at the relationship between opioid-related payments and prescribing. These studies are Hadland et al. (2017), Hadland et al. (2018), and Nguyen et al. (2019b).

Using Open Payments database, where payments made by drug companies to physicians are recorded, Hadland et al. (2017) calculate that 375,266 non-research, opioid-related payments were made to 68,177 US physicians totaling $46,158,388 between 2013 and 2015. They also find that one in twelve physicians received an industry payment involving an opioid, with most common types of payments belonging to the food and beverage category, comprising 93.9% of all payments. In a follow-up study, they link the Open Payments data to Medicare Part D opioid prescribers to show that the receipt of any non-research payment related to an opioid product in 2014 was associated with 9.3% more opioid claims in 2015 (Hadland et al., 2018). Nguyen et al. (2019b) also uncover positive association between opioid-related promotions and opioid prescribing, finding that prescribers who receive promotional opioid payments prescribe 8,784 more opioid daily doses per year relative to physicians who did not receive any marketing payments. However, these studies do not account for the endogeneity of opioid-related industry payments to physicians. Since pharmaceutical sales representatives target doctors who are most likely to prescribe their products, such as physicians who are already high-prescribers of opioids and/or physicians who have patient populations with high demand for opioid drugs, not accounting for this selection will lead to estimates that overstate the effect of opioid marketing to physicians.[4]

As various policy initiatives designed to reduce overall opioid prescribing and increase substitution from generic to ADF opioids have been put forth, the question of how direct-to-physician marketing affects physician's opioid prescriptions and which type of opioids are affected (generic, patented, or abuse-deterrent) grows in relevancy. The answer to this question may inform about the effectiveness of policies that restrict physician access to the pharmaceutical company representatives and access to potentially valuable drug

[4]Datta and Dave (2017) look at a very specific class of drugs designed to treat herpes viral infections. Mizik and Jacobson (2004) examine three unknown drugs produced by one, undisclosed, firm. Thus, while these studies control for high-prescribing physician selection, the estimated effects in these two studies may not be applicable to direct-to-physician opioid promotion.

information that such interactions may provide.[5] Importantly, examining how direct-to-physician marketing may affect susceptible-to-abuse generic prescribing, may provide important insights about possible channels through which pharmaceutical interactions may affect the risks of addiction and mortality from overdoses.

My findings suggest that opioid promotion to physicians may hinder the current state and national efforts to reduce opioid prescribing. Furthermore, while policymakers promote abuse-deterrent opioids as a way to reduce the risk of opioid misuse and addiction, the marketing of these safer medications may have the opposite effect. Since detailing visits drive the spillovers on misuse-prone generic prescribing, restricting or limiting opioid detailing may be an appropriate policy response in the battle with the opioid epidemic in the United States. Alternatively, the practice of "academic detailing", where trained clinical educators visit physicians to discuss safest and most effective medications for patients based on current research, may be a way to get important opioid information to physicians and counteract the effect of marketing by opioid producers (Larson et al., 2018; Liebschutz et al., 2017).

This paper proceeds as follows. In Section 2.2, I discuss the abuse-deterrent formulations (ADFs) and the specifics surrounding Medicare Part D population. Data sources and sample construction are discussed in Section 2.3. In Section 2.4, I present the main empirical strategies. The results are shown and discussed in Section 2.5. In Section 2.6, I introduce various robustness checks and conclude in Section 2.7 by discussing some implications of my results.

2.2 Background

2.2.1 Abuse-Deterrent Formulations and Policy

Policymakers consider the development of abuse-deterrent formulations (ADFs) of prescription opioids as an important strategy to combat the opioid epidemic. The main

[5]There exist two prevailing views on the influences of detailing visits. One view asserts that pharmaceutical interactions with physicians influence their prescribing in a way that is detrimental to patients' welfare, since they tend to promote excessive prescribing of costly brand-name drugs. On the other hand, interactions with pharmaceutical companies provide physicians with valuable information, such as information on new drugs with new indications, as well as how they may interact with existing drugs and dosage details, which positively affects consumers.

goal of ADFs is to deter an individual from chewing, inhaling, or intravenously injecting the drugs, which give the individual a greater degree of "rewarding" effect but also rapidly elevate the blood pressure and increase the risk of respiratory depression and a fatal overdose. In addition, non-oral routes of administration are associated with an increased risk of addiction and abuse, as well as a variety of other health consequences, including damage to nasal/oral structures and blood-borne infections (Dunn et al., 2010; Katz et al., 2011; Raffa and Pergolizzi, 2010). Because opioid medications continue to play a vital role in pain management, ADFs may be a valuable component of providers' opioid risk management plans (along with patient education, prescription drug monitoring programs, and other guidelines/policies). In order to encourage a shift from the traditional opioid formulations to ADFs, the U.S. Food and Drug Administration (FDA) released 43 new or revised product-specific guidance documents to push generic ADF development (U.S. Food and Drug Administration, 2018).

However, ADFs are not yet commonly prescribed, largely because these new formulations are available only as patented products, which are more expensive than a large number of non-abuse-deterrent opioids that are available in generic formulations. Furthermore, many insurance companies will not cover ADFs and/or limit their reimbursement, which deters doctors from prescribing them. For example, the Institute for Clinical and Economic Review (ICER) reviewed 2017 coverage policies and formularies for six New England state Medicaid programs, CMS, and 12 major "Silver-level" plans on individual marketplaces across New England, and identified coverage policies for four of the nine (available in 2017) ADF opioids.[6] They found that all plans maintained quantity limits for these opioids and the majority required prior authorization.[7] Several studies have examined the unwillingness of the insurance companies to cover tamper-resistant and ADF opioids, with access limitations that include requirements by the insurance carriers for patients to provide diagnosis of addiction, documentation of high-risk for abuse, and/or exclusions from formularies (Argoff et al., 2011; Brushwood et al., 2010; Schatman and Webster, 2015). In addition to prior authorization and other requirements, it is common for the commercial insurance plans to mandate that patients try generic equivalents or

[6]OxyContin, Xtampza, Hysingla ER, and Embeda are the four ADFs identified.

[7]Prior authorization requirement means that the doctor must obtain approval from the insurance plan in order to prescribe the drug.

preferred brand name opioids first (Institute for Clinical and Economic Review, 2018). By encouraging utilization of relatively cheaper but abuse susceptible generic formulations, such "fail-first" policies may be undermining the national efforts to curb unsafe opioid prescribing.

Some parts of the multipronged, national strategy to combat the opioid epidemic include educating physicians to decrease prescribing of opioids, shortening the duration of opioid therapy, carefully monitoring prescribing, as well as mandatory substitution of generic opioid prescriptions with ADFs. State governments also tackle the epidemic in various ways, including the creation of executive-led task forces, physician education, prescription drug monitoring programs (PDMPs), and the allocation of more funding for abuse treatment options. Importantly, to increase patients' accessibility to ADFs, several states have introduced legislation mandating that ADFs be available on formularies and requiring that they be covered by the insurance companies. However, data on the impact of such policies is limited and inconsistent (Institute for Clinical and Economic Review, 2018). In 2015, the FDA issued a non-binding recommendation encouraging manufacturers to produce abuse-deterrent opioids, stating that "FDA considers the development of ADFs a high public health priority." (FDA, 2015)

2.2.2 Medicare Part D

Because my study utilizes data on Medicare Part D claims, it is important to understand prescription opioid use and abuse in Medicare Part D beneficiary population. As people age, they become more likely to develop a painful chronic condition, involving degeneration in bones, joints, and muscles (Molton and Terrill, 2014). While about 30% of the general population reports pain, among older adults it is higher, with about 40% of the elderly reporting pain (Le Roux et al., 2016). According to the Office of Inspector General, about one in three beneficiaries received at least one opioid prescription through Medicare Part D in 2017. That year, Medicare Part D paid for 76 million opioid prescriptions, which amounts to about 5.4 opioid prescriptions per beneficiary. For comparison, 3.4 opioid prescriptions per person are written in the general U.S. population. About 1 in 10 Part D beneficiaries receive opioids on a regular basis (meaning, they are taken for 3

or more months), which substantially increases the risk of opioid dependence (HHS OIG Data Brief, 2018). In 2017, a total of 458,935 Part D beneficiaries received high amounts of opioids (average morphine equivalent dose of greater than 120mg a day for at least 3 months), who did not have cancer and were not in hospice care.[8] In addition, some states had higher proportions of Part D beneficiaries receiving prescription opioids compared to the national averages. While many of these prescriptions may have been necessary, such high numbers suggest that prescribing and utilization of these opioids may have been inappropriate.

While not the largest age group misusing opioids, older adults (aged 65+) are exhibiting sharp increases in mortality and hospitalization rates due to prescription opioid misuse (Benson and Aldrich, 2017). The Medicare population has among the highest and fastest-growing opioid use disorder rates,[9] with more than 6 of every 1,000 beneficiaries being diagnosed with opioid addiction (Lembke and Chen, 2016). Additionally, older adults with an opioid use disorder may be at a higher risk of death compared to the younger adults (Larney et al., 2015). Therefore, information regarding how patented opioid marketing influences the types of opioids being prescribed to the elderly may be important for policymakers' understanding about patient access to safer ADF medications.

2.3 Data

The majority of my data come from two databases maintained by the US Centers for Medicare and Medicaid Services (CMS). One contains all prescription claims reimbursed under the Medicare Part D program, which includes the number and type of prescriptions written by individual physicians nationally. The other, the Open Payments database, contains millions of records of payments and gifts made by pharmaceutical and medical device companies to doctors and teaching hospitals in the US.

The Open Payments program was established under the Physician Payments Sunshine Act as part of the Affordable Care Act in order to give the public more information about the financial relationships between physicians and drug and medical device manufacturers. Specifically, the program is designed to promote transparency about financial ties between

[8] In 2017, Medicare covered 45 million beneficiaries.
[9] Opioid use disorder is sometimes referred to as "opioid addiction".

medical care providers and the industry, to inform on the nature and extent of such relationships, and to help prevent inappropriate influence on research, education, and clinical decision making (CMS.gov, 2016). Starting in mid-2013, all payments made by the applicable manufacturers and group purchasing organizations to physicians and teaching hospitals must be reported to the Centers for Medicare & Medicaid (CMS), and are published in the Open Payments database.[10] The physicians are able to review and dispute the payments about them before it is published on the website. The Open Payments database contains information on the type of payment made by the manufacturer to a physician, physician's name and address, the monetary value of the transfers, the name of the firm making the payment, as well as the drug that is associated with the payment. In the 2014-2017, there were 936,891 US physicians with at least one pharmaceutical (or medical device) payment.

In order to identify promotional interactions related to patented opioids, I utilize the list of opioid drugs that comes from the CMS's Prescriber Drug Category List for years 2014-2017.[11] Because prescriptions written for patented drugs cannot be substituted for generics by the pharmacist, only patented opioid promotional payments were used to study the effect on physicians' prescribing patterns.[12] I determined which opioid drugs on the CMS list were under patent for the time-frame of the study by using the U.S. Food and Drug Administration's Orange Book and DrugPatentWatch.com. If an individual payment in the Open Payments database contained an opioid drug name that matched a patented opioid drug name on the CMS list, then the marketing interaction was related to the promotion of patented opioids. Table B.1 contains the list of patented opioid drugs used to define patented opioid-related interactions.

Table B.2 contains detailed information on the type of opioid-related payments included in my data for the period 2014-2017.[13] The most common way to promote drugs

[10]Payments/transfers of value that are less than $10 do not need to be reported, unless the total annual value of payments provided to a physician or teaching hospital by a single applicable manufacturer or GPO is more than $100 (CMS.gov, 2016).

[11]The list is based upon drugs included in the Medicare Part D Overutilization Monitoring System (CMS.gov, 2019).

[12]A minuscule amount of opioid payments involved the promotion of off-patent, generic opioids, usually as part of patented advertising. I also created separate generic-interactions variables and account for it in several specifications.

[13]This study is limited to payments that may target physician prescribing and do not include research and non-equity payments, similar to other studies on direct-to-physician promotion.

to physicians is through pharmaceutical detailing, or sales pitches where drug details about safety, efficacy, and side effects are presented to the physician by a pharmaceutical sales representative, usually over a meal. Detailing is considered pharmaceutical firms' "highest-impact promotional weapon" (Campbell, 2008) and is captured by the category "Food & Beverage" in the dataset. Other types of interactions include payments for serving as faculty, speaking and consulting fees, payments related to services for continuing education programs, education-related payments, gifts, honorary payments, and travel and lodging payments.[14] During this 4-year period physicians received 565,892 patented opioid-related payments that were worth $41.9 million.

I use Medicare Part D Provider Utilization and Payment Data to capture physician's prescribing patterns, available on the CMS website (CMS.gov, 2019). This physician-level, publicly available dataset contains information on all Part D final-action prescription drug claims for Medicare beneficiaries.[15] In addition to information on counts and costs for individual physicians' prescription claims, this Part D database contains provider names, business locations, specialty, national provider identifiers (NPIs) and patient-population information for 1,325,181 Part D prescribers.[16] Because the Part D claims database utilizes NPIs to identify prescribers and the Open Payments database uses its own identifiers for physicians, I linked the physicians listed in the Open Payments to Part D prescriber data using physician names and zip codes of practice location. I was able to match 726,288 Open Payment prescribers using this matching technique.[17]

For additional information on providers I used publicly available Physician Compare data. This dataset contains various performance scores for doctors, along with other characteristics designed to help Medicare patients and caregivers make informed decisions

[14]The full list of payment categories in the Open Payments data and their definitions are available at https://www.cms.gov/OpenPayments/About/Natures-of-Payment.html.

[15]Submitted by both Medicare Advantage Prescription Drug plans and by stand-alone Prescription Drug Plans. While the dataset does not include prescriptions covered by payers other than Medicare Part D, it is the only publicly available data with information on both the prescribers and drug claims (Nguyen et al., 2019a).

[16]A small proportion of these prescribers may be organizational providers, such as nursing homes, group practices, and physician centers.

[17]Out of 210,603 unmatched Open Payment prescribers, only 5,693 physicians had any opioid payment for the time-frame of the study, averaging 2 interactions per year with $171 average spent on each doctor per year in opioid-related payments.

about providers by giving them the ability to search for and compare clinicians who participate in Medicare (Data.Medicare.gov, 2019).

Physicians who moved from one zip code to another during the period of the study could potentially have unusual prescribing patterns and, thus, were excluded from the sample. After removing physicians who moved during the time-frame of the study, providers that are in the dataset for only one year and doctors with missing control variables, I ended up with 663,922 US providers. However, since the central analysis relies on the within-physician variation, the main sample of anaysis is restricted to physicians who had at least one industry interaction involving a patented opioid for years 2014-2017 or 48,276 US providers (about 7.3% of Medicare physicians). This estimate is very similar to calculation of Hadland et al. (2018) who find that about 7% of physicians who prescribed opioids under Medicare Part D had at least one non-research opioid related payment in 2014. The summary statistics for the full and the main samples are presented in Table B.3 (the "All" and "Ever Interacted" columns, respectively).

2.4 Methodology

The following equation is used to estimate the effect of physician-directed marketing interactions on the prescriptions of opioid drugs:

$$Claims_{i,z,t} = \beta Interactions_{i,z,t} + \delta X_{i,z,t} + \lambda_{zt} + \theta_i + u_{i,z,t} \tag{2.1}$$

Equation 1 denotes that the number of opioid claims (*Claims*) by physician i in zip code z in year t depends on the number of opioid-related interactions with the pharmaceutical companies (*Interactions*). The parameter of interest is β, which captures the impact of physician-industry interactions related to patented opioids on opioid prescribing habits of the physician. In additional specifications, I add the quadratic term (*InteractionsSQ*) to examine potential non-linearities. The two dependent variables of interest are the number of patented opioid claims and generic opioid claims.[18]

[18]Generic opioid claims may include branded drugs, but these branded opioids were not patented at the time of the study. Any branded medications that are not patented can be substituted for the generic by the pharmacist, and in many states, the law requires the pharmacies to do so.

It is crucial to address the selection of physicians into interactions with pharmaceutical firms. High prescribers of opioids, whether generic or brand-name, or those with higher probability of prescribing opioid medications (for example, physicians in certain specialties or in market areas with higher demand for opioids), are more likely to be targeted by the pharmaceutical company representatives. As Table B.3 indicates, there are differences across the observed characteristics of physicians who have encounters with firms marketing opioid drugs ("Ever Interacted" column) and the average physicians ("All" column). The interacting physicians have higher level of both generic and patented opioid claims, write more non-opioid prescriptions, have more patients and work with fewer other doctors than physicians who did not have any industry relationships in 2014-2017. Since the observed characteristics of physicians with industry interactions differ from physicians with no interactions, this suggests that unobserved doctor differences are important to consider. Unobserved preferences such as brand loyalty, risk tolerance, tradeoffs among counter-indications, efficacy, and long-term use, potentially play an important role in both the physicians' prescribing decisions and the level of interactions with the pharmaceutical firms (Datta and Dave, 2017). Thus, my estimation strategy relies on within-doctor variation, where physician fixed effects (θ_i) account for these potentially confounding observed and unobserved time-invariant factors. Additionally, the inclusion of interacted zip code by year dummy variables (λ_{zt}) controls for zip code specific, time-varying demand shocks that may affect both prescribing and pharmaceutical marketing activity. For example, local shocks can be related to factors such as zip code level changes in prescribing, disease prevalence, area demographics, economic conditions, marketing levels, unobserved seasonal and national trends (such as shifts in Medicare Part D drug coverage that affect all beneficiaries), policies related to opioid prescribing, and pharmaceutical promotion trends aimed at consumers. Thus, the source of my model's identifying variation comes from within-doctor changes over time that differ across physicians within the same zip code. Because utilizing within-physician, within-zip code variation allows to control for regional, zip code-specific opioid demand shocks that may vary from year to year, the main threat to this identification strategy comes from physician-specific (non-regional) demand shocks not otherwise accounted for by the control variables.

Opioid prescribing also depends on the patient population of the physician. Not only are doctors with more elderly, chronic-pain-prone patients expected to write more opioid prescriptions, but they are also more likely to be targets for opioid marketing. Physicians working in certain settings (for example, hospitals or academic medical centers) may face restrictions on interactions with pharmaceutical companies and prescribe opioids in systematically different ways. Thus, to account for these time-varying factors, X contains a vector of variables such as physician i's number of claims, total number of doctors that work with i in the same group or practice, number of Part D beneficiaries (as well as Part D beneficiaries over age 65), number of low-income subsidy claims, number of beneficiaries who qualify to receive both Medicare and Medicaid benefits (dual beneficiaries), number of black beneficiaries, and number of female beneficiaries.

Advertising literature suggests that the effect of promotion may last beyond the time of the promotional interaction (Datta and Dave, 2017). The effects may persist over time due to various factors, such as learning, reminders, and inertia (persistence in prescribing habits). Various studies utilizing distributed-lag models as well as other specifications find that the effect of non-pharmaceutical promotion on sales lasts between under a year to fifteen months (Bagwell, 2007). Research on direct to consumer marketing of pharmaceutical drugs suggests that the effects of promotion depreciate within six months to a year (Iizuka and Jin, 2005; Ling et al., 2002). To measure the persistence of opioid-related interactions, I estimate the following equation:

$$\begin{aligned} Claims_{i,z,t} = \beta_1 Interactions_{i,z,t} + \beta_2 Interactions_{i,z,t-1} + \beta_3 Interactions_{i,z,t-2} \\ + \gamma C_{i,z,t} + \lambda_{zt} + \theta_i + v_{i,z,t} \end{aligned} \tag{2.2}$$

Here the coefficients capture the effect on i's current opioid claims of promotional interactions in the current year (β_1), one year after the interaction (β_2), and two years after the interaction (β_3). In addition to control variables from equation 1, C is a vector containing variables that control for the number of generic-only opioid promotional interactions and the number of joint generic-patented opioid interactions. *Interactions* captures the effect of patented-only promotional payments.

I expect the promotion of ADFs to have a different effect on opioid claims compared to non-ADF interactions. For example, ADF promotion is likely to inform physicians about

the relative safety of ADF opioids compared to misuse-prone generics and non-abuse-deterrent formulations. If physicians substitute away from non-ADF opioids as a result of ADF marketing, I would expect the spillover effect on generic and non-ADF claims to be negative. On the other hand, costlier abuse-deterrent drugs may face insurance coverage access limitations and "fail-first" requirements. Because "fail-first" policies promote the usage of generic opioids before more expensive ADFs are covered, any ADF-specific promotional spillovers on generic prescribing may be positive and larger than interactions related to non-ADF opioids. To examine how interactions related to the various types of promotion affect claims, I estimate the following equation:

$$\begin{aligned} Claims_{i,z,t} = {} & \alpha_1 ADF_{i,z,t} + \alpha_2 ADF_{i,z,t-1} + \alpha_3 ADF_{i,z,t-2} \\ & + \alpha_4 NonADF_{i,z,t} + \alpha_5 NonADF_{i,z,t-1} + \alpha_6 NonADF_{i,z,t-2} \\ & + \alpha_7 Both_{i,z,t} + \alpha_8 Both_{i,z,t-1} + \alpha_9 Both_{i,z,t-2} \\ & + \gamma C_{i,z,t} + \lambda_{zt} + \theta_i + e_{i,z,t} \end{aligned} \tag{2.3}$$

In this specification the *Interactions* variable is disaggregated into the number pharmaceutical interactions that involve the discussion of ADF opioids only (ADF), the number of promotional interactions involving non-ADF patented opioid drugs only ($NonADF$), and the number of payments that listed both ADF and non-ADF patented opioids being promoted ($Both$). All other variables are the same as in equation 2. This specification allows me to examine how different types of interactions affect ADF, non-ADF, and generic opioid claims, captured by $Claims_{i,z,t}$. In addition to examining the differential effects on generic prescribing, this specification allows to examine the effectiveness and spillover effects of ADF vs. non-ADF promotion on ADF and non-ADF claims.

2.5 Results

Table B.4 displays the coefficient estimates for the effect of interactions on physician's patented opioid claims. The coefficients across all specifications of the model imply that interactions with the opioid industry have a positive effect on the quantity of physician's patented opioid claims. Column 1, the specification without the control variables, indicates that each interaction involving a patented opioid increases physician's patented

opioid claims by about 3 per year. On average, physicians have 17.66 patented claims per year, so the estimate corresponds to about a 17% increase in the average patented opioid claims. The coefficient estimate is highly significant and adding controls and interacted zip code by year fixed effects in columns 2 and 3, respectively, reduces the estimates slightly to 2.1. Specification 4, the main specification, fully exploits the panel data and accounts for physician fixed effects, which capture a physician's observed and unobserved characteristics and preferences. When physician fixed effects are added, the average effect from an interaction falls substantially, with each interaction inducing the physician to generate 0.7 more patented opioid claims (or 4% of the average). The drastic reduction in the coefficient value as doctor fixed effects are added implies that physicians are likely targeted by firms based on physician heterogeneity in observed and unobserved characteristics and preferences, rather than merely zip code-level geographic heterogeneity. In column 5 the quadratic term is not statistically significant, implying that the average effect of each interaction on patented opioid prescriptions is relatively linear.

The results in Table B.4 indicate that industry interactions associated with marketing of patented opioids have a statistically significant effect on patented opioid prescribing, with each interaction increasing physician's prescribing by 0.7 patented opioid claims. Since the average doctor in the main sample has 3.19 interactions with opioid producers per year, this estimate implies that, on average, these interactions will increase a physician's patented opioid claims by 12.8% per year. This provides evidence that firm interactions with physicians indeed push them toward prescribing more patented (and possibly costlier) opioid drugs. These estimates are substantially lower than in specifications that do not account for endogeneity, suggesting that a good amount of the observed association between direct-to-physician promotion and opioid sales reflects unobserved selection of physicians into industry relationships.

Table B.5 presents the regression estimates for the average effect of interactions with the opioid industry on a doctor's generic opioid claims. The results inform about whether direct-to-physician marketing of patented opioids has any spillover effects on generic opioid prescribing. All specifications suggest that such spillovers are indeed present, with opioid industry interactions positively affecting physicians' generic (non-patented) opioid claims. Column 1 shows that each interaction is associated with an average increase of 28 generic

claims per year, or about 6% of the average generic claims. When control variables and interacted zip code by year fixed effects are added to the model in columns 2 and 3, respectively, the coefficient measuring the effect of industry interactions falls to about 12 claims. The average effect of an interaction declines further to 5.3 (or 1% of the average) when physician fixed effects are added to the model in column 4. This suggests that physician-specific heterogeneity is an important consideration. Because in rare instances generic opioids were listed as being part of the promotion of patented drugs, it may be a concern that generic promotion could be driving the spillover effect on generic prescribing. To address this potential issue I examine the effect promotions that did not involve any generic opioids.[19] The results, presented in column 5, are very similar those in column 4, indicating that the spillovers are not the result of generic-related marketing.

The estimates in Table B.5 suggest that the direct-to-physician marketing of patented opioids has significant and substantial spillover effects on generic opioid prescribing, with doctors increasing their generic opioid claims by 3.6% per year[20] as a result of pharmaceutical interactions related to patented opioids. Therefore, doctors are prescribing more generic opioid drugs instead of switching patients away from generics when they learn about the new patented (and in some cases safer abuse-deterrent) opioid medications.

While 94% of the promotional interactions in my dataset are detailing visits (proxied by the "Food & Beverage" category), other types of promotional activities may nevertheless influence physician prescribing behavior. To see whether the effects differ depending on the type of interaction, I disaggregate the *Interactions* variable into the number of detailing interactions (*Food & Beverage Interactions*) and the number of other types of promotional interactions (*Other Interactions*).[21] Additionally, in order to test whether the value of the payment matters, I include the payment amount received by the physician for an opioid-related interaction. The results are presented in Table B.6.

The coefficient estimates on detailing visits do not substantially differ from the main specification results, with each detailing visit increasing patented prescribing by about 0.6 claims and generic prescribing by about 6.4 claims per year. These estimates imply that the primary results in Tables B.4 and B.5 are primarily driven by detailing pharma-

[19] In this specification, the control variables include the number of generic opioid-related interactions.
[20] Based on the 3.19 interactions per year average.
[21] See Table B.2 for more information on the types of interactions in the dataset.

ceutical visits. This finding is not particularly surprising given that the sole objective of pharmaceutical detailing is to induce physicians to prescribe the advertised drug, unlike other types of interactions.

The results produced by Grennan et al. (2018) suggest that while receiving a meal leads to an increase in claims for the promoted drugs, there are no marginal returns to higher-value meals. However, my results suggest that after controlling for promotional visits, higher value meals do increase patented claims more than lower-value detailing. I find that for every $1 increase in the meal value, the doctor will generate 0.01 more patented claims. The average spending on promotional detailing is $48.29 per physician per year in my dataset, and each doctor has 3 detailing visits per year on average. This implies that the average detailing visits combined with the money spent on food and beverages will increase physician's patented claims by about 2.34 or by about 13.3%.[22]

The results indicate that non-detailing interactions such as education-related speaking, consulting, travel-related activities, and gifts do not have a statistically significant effect on opioid prescribing. Although column 2 indicates that higher-paid activities related to patented opioids induce physicians to prescribe fewer generics, the magnitude is extremely small - a $1 increase in the amount paid to the physician decreases generic prescribing by 0.004 claims (or 0.00001% of their average generic claims). This implies that the average non-detailing payments to physicians ($187.96) will decrease generic prescribing by 0.81 opioid claims or 0.2% of the physician's average generic claims. In these non-detailing interactions physicians are likely spending some time on researching and preparing materials related to newer and safer opioid drugs, so the slight negative effect on unsafe generic prescribing may be expected.

Prior direct-to-physician advertising literature indicates that the effects of promotion on prescribing generally go away within two years. To shed light on the persistence of promotional effects, Table B.7 presents the coefficient estimates for equation 2. The first column estimates suggest that the effect of patented promotion on patented opioid claims dissipates after about two years, consistent with prior literature's findings. While current-year interactions increase current-year patented opioid claims by about 0.7 claims, the interactions from one year ago increase patented claims by about 0.2, and interactions

[22] 0.00957(48.29)+0.627(3)=2.343.

from two years ago have no statistically significant effect on patented prescribing. On the other hand, the generic spillover effects remain persistent over the years. The results in the second column indicate that current-year interactions increase current generic claims by 3 claims per year, interactions from one year ago and two years ago increase current generic opioid prescribing by about 2 claims. These estimates suggest that not only are doctors prescribing more unsafe generic opioids as a result of patented marketing, but that these effects continue to linger over the years.

One explanation for positive generic spillovers is that doctors who want to prescribe ADF drugs as a result of direct-to-physician ADF marketing must first prescribe generic opioids because of "fail-first" insurance policies, leading to positive spillovers on generic opioid claims. On the other hand, physicians may not face stringent insurance constraints when they are prescribing non-ADF drugs. It is also possible that physicians who are initially induced to prescribe more ADF drugs, as they learn about their safer properties from the sales representatives, end up switching their patients to generics as a result of patents' unwillingness to deal with ADF drugs' high cost and difficulty with access. To examine in more detail the heterogeneity of the direct and spillover effects for ADF vs. non-ADF interactions, I estimate equation 3. Figures B.6-B.11 along with Table B.8 present the results.

Figures B.6 and B.7 show the effect of promotional interactions on the claims of the drugs that are being promoted. The results shown by Figure B.6 indicate that each current-year interaction involving discussion of only ADF opioids increases current-year ADF claims by about 0.45 and interactions from one and two years ago increase ADF claims by 0.38 and 0.35, respectively. These results suggest that the effects of ADF-only marketing are very persistent throughout the time-frame of the study. On the other hand, non-ADF patented promotion does not display the same persistence, as shown by Figure B.7. While each current-year non-ADF promotional interaction increases non-ADF prescribing by 0.42 claims per year, the effects of past interactions on current claims are substantially reduced. For example, non-ADF promotions from one and two years ago increase current year non-ADF claims by only 0.14 and 0.17, respectively.

Figures B.8 and B.9 display the non-generic spillover effects of each type of marketing. The results suggest that ADF marketers are able to dissuade doctors from prescribing non-

ADF patented opioids. Figure B.8 shows that current ADF-only marketing does not have any effect on current non-ADF claims. Additionally, past ADF-only marketing reduces the likelihood that a non-ADF opioid is prescribed, with promotions taking place one year and two years ago decreasing current non-ADF prescribing by about 0.2 claims per year. These estimates suggest that doctors may be learning about the safety features of abuse-deterrent opioids from the pharmaceutical sales reps, choosing to prescribe less patented drugs which do not prevent misuse. On the other hand, non-ADF patented promotion is not as successful in preventing doctors from prescribing ADF drugs. As Figure B.9 shows, each current non-ADF-related interaction increases current ADF claims by 0.3 on average. This spillover effect tapers off over time, with non-ADF interactions from a year ago increasing current ADF claims by about 0.2, and non-ADF promotions from two years ago appearing to have no effect on current ADF claims.

Figures B.10 and B.11 show the spillover effects of ADF and non-ADF patented marketing on generic prescribing. Coefficient estimates suggest that ADF-only marketing has bigger spillover effects on current abuse-prone generic prescribing relative to non-ADF interactions - current ADF-only interactions increase current generic claims by about 4, while current non-ADF promotions increase generic prescribing by only 1.5 claims per year. In addition to having higher current spillover effects on non-safe prescribing, ADF-only marketing spillovers are also more persistent through the years. ADF-only interactions from one and two years ago increase generic prescribing by 2.3 and 2.7 generic opioid claims, respectively, while past non-ADF interactions increase current generic opioid prescribing by 1.6 and 1.7 claims.

Together the figures imply that, first, ADF-only marketing is more effective than non-ADF promotion. ADF-only interactions have a highly persistent impact on ADF claims, while the effect from non-ADF marketing on non-ADF claims does not appear to be as lasting. Furthermore, ADF-only promotion appears to be successful in persuading doctors to prescribe ADF drugs and avoid non-ADF patented opioids. Second, according to the estimates, ADF marketing may come with unintended adverse consequences on public health. ADF-only opioid promotion has greater and more persistent spillover effects on unsafe generic opioid prescribing. This result is consistent with the fact that ADF prescribing involves insurance access restrictions such as “fail-first” policies that encourage

substituting toward cheaper generics. It appears that physicians are substituting away from the traditional patented formulations and toward ADF opioids as a result of ADF-only marketing, which likely emphasises to physicians the relative safety of abuse-deterrent formulations. However, because abuse-deterrent opioids are subject to limited insurance plan coverage and plan-specific rules that require trying generic opioids before an ADF is covered, the ADF-related interactions also produce larger spillover effects on generic claims relative to other types of opioid interactions.[23]

2.6 Robustness

Including physician and zip-code-by-year fixed effects in my main specification allows me to account for observable and unobservable physician characteristics that may lead to selection, as well as to control for time-varying local opioid demand shocks that may affect the prescribing behavior of doctors and the number of pharmaceutical interactions. However, the fixed effects strategy may not fully account for the endogeneity if a doctor experiences a physician-specific opioid demand shock that is unrelated to changes in demand at the zip code level and is at the same time correlated with the pharmaceutical marketing. For example, this could occur if a physician experiences a sudden increase in demand for opioids that is not encountered by any other physician in the same zip code and that induces a visit from an opioid sales representative. Then, the physician-specific increase in demand could be wrongly attributed to the promotional visit. However unlikely such a scenario may be, I check my main specification results by employing an instrumental variable approach. Additionally, I estimate equation 1 on several different samples of physicians to increase confidence that the results are not driven by outliers.

2.6.1 IV Identification Strategy

The instrumental variable model identification strategy is similar to the approach taken by Grennan et al. (2018) and relies on the fact that drug manufacturers allocate their marketing budget based on certain aggregate market characteristics. For exam-

[23] Non-ADF patented opioids may also be subject to limiting insurance policies, however, not to the same extent as ADF opioid drugs.

ple, markets with many opioid-prescribing providers and larger pain-prone population are more likely to have bigger direct-to-physician marketing budgets allocated to them.[24] The firms' marketing models are based on detailed data that includes physicians' prescribing history, physician and practice characteristics, and past history of physician's interactions with the pharmaceutical firms (Campbell, 2008). Once the budgets are allocated and pharmaceutical representatives are assigned to their respective regions, it is up to the individual sales reps to target "high-value" physicians. Thus, after conditioning on characteristics that make a given physician likely to be targeted by the sales representative, the characteristics of other physicians in the geographic market (attractiveness of other physicians to the pharmaceutical reps) can serve as instruments for the physician's interactions with the pharmaceutical company, and should not affect the given physician's prescribing directly. I conduct the analysis using a full sample of physicians. Equations 2.4 and 2.5 present the first and the second stages of the IV approach.

$$\text{Stage 1}: Interactions_{i,z,t} = \gamma Interactions_{z,t(-i)} + \delta X_{i,z,t} + v_z + \tau_t + \theta_i + e_{i,z,t} \tag{2.4}$$

$$\text{Stage 2}: Claims_{i,z,t} = \phi \widehat{Interactions}_{i,z,t} + \delta X_{i,z,t} + v_z + \tau_t + \theta_i + u_{i,z,t} \tag{2.5}$$

I use zip code level variables ($Interactions_{z,t(-i)}$) to serve as instruments for opioid-related interactions with the pharmaceutical firm . The instrument set includes the total number of opioid-related interactions in physician i's zip code (excluding i's opioid-related interactions) and the total value of payments made to other physicians in i's zip code by any pharmaceutical or medical device firm. These zip code level instruments should be correlated with physician i's opioid-related interactions, but should not affect i's opioid claims directly after controlling for i's practice and patient characteristics. Instead of using within-physician, within zip code differences to identify the effect of pharmaceutical marketing (my main specification), the advantage of using this strategy is that the source of identifying variation comes from the other physicians within the zip code. This estimation strategy does not allow for zip code by year fixed effects, since this is the variation I depend on. However, zip code fixed effects (v_z), year fixed effects (τ_t), and physician

[24] Pharmaceutical sales regions are defined by geography and other categories such as therapeutic area (Campbell, 2008).

fixed effects (θ_i) are included separately. Vector $X_{i,z,t}$ contains covariates defined in the main specification.

Table B.9 present the Two-Stage Least Squares (2SLS) results. The first stage F statistic of 84.0 suggests that the instruments are strong and Hansen J test of overidentifying restrictions implies that they are also valid. The second stage coefficient estimate for the effect of interactions on patented claims is 0.702, which is identical to the preferred specification in Table B.4 (column 4). The average effect on generic claims is 6.837, compared to a slightly lower coefficient estimate of 5.3 from Table B.5 (column 4). Overall, the IV coefficient estimates provide confidence in the results of the preferred, fixed effects specification shown in Tables B.4 and B.5.

2.6.2 Other Robustness Checks

In order to check whether the results are driven by outliers, I estimate equation 1 on samples of physicians that exclude extreme values. Since doctors who have a very high number of yearly interactions with opioid marketers may be induced the most to prescribe more opioids, Table B.10 presents the results for a sample that excludes the physicians with highest 1% of opioid interactions. The results are nearly identical to coefficients from the main specifications. The coefficient estimate on patented claims is slightly lower, with each interaction increasing patented claims by 0.55 (compared to 0.7 in the main estimation). The coefficient estimate on generic claims is slightly higher, increasing from 5 to 6.6 in the specification without outliers. To see if very high payments to doctors (at each marketing interaction) are driving the effect of marketing on opioid claims, Table B.11 presents coefficient estimates for the sample that excludes doctors with top 1% of promotional payment amounts related to opioid drugs. Once again, the coefficient estimates are virtually unchanged, with each interaction increasing patented claims by 0.6 and generic claims by 7. The coefficient estimates in Tables B.10 and B.11 suggest that the main specification results are not driven by physicians receiving large opioid payments or by prescribers with unusually high frequency of industry interactions.

Additionally, in order to check if the results may be driven by any one opioid-producing firm's ability to market drugs to doctors, I separate the *Interactions* variable into the

number of interactions for each firm present in my data. The results are presented in Table B.12. The coefficient estimates suggest that while the effects vary from firm to firm, the results are not driven by just a few opioid producers.

2.7 Conclusion

This study informs the direct-to-physician marketing literature by examining the effect of promotional industry interactions related to patented opioid drugs on patented and generic opioid prescribing patterns while fully exploiting physician level longitudinal data for years 2014-2017. I control for high-prescriber selection into marketing interactions by utilizing physician fixed effects, while zip-code-by-year fixed effects account for any time-varying regional opioid demand shocks that may affect both prescribing patterns and opioid marketing strategies. The results indicate that direct-to-physician patented opioid marketing increases opioid prescribing. These effects are driven by detailing visits and appear to be increasing in the value of meals provided to physicians during the sales pitch. The findings suggest that the average number of detailing visits together with the average cost of the meal induces physicians to generate 13.3% more patented opioid claims per year.

Not only do the results indicate the presence of positive and statistically significant effects on patented opioid claims, but they also show that patented promotion causes positive and persistent spillover effects on abuse-prone generic prescribing in Medicare Part D. Instead of substituting away from unsafe prescribing, doctors end up increasing their generic claims by about 3.6% per year as a result of patented direct-to-physician advertising.

The caveat of these findings may be that the effects are pertinent to physician-industry promotional interactions in the market for opioid drugs and not relevant for other pharmaceuticals. Nevertheless, the results carry important implication for nation-wide policy strategies used in the battle with opioid misuse and addiction. According to the estimates in this study, the supply of both patented and generic opioids may be increased by the direct-to-physician marketing of opioids, undermining the current federal and state efforts to reduce opioid prescribing. Importantly, the promotion of safer abuse-deterrent

opioid drugs may come with unintended consequences in the form of wider prescribing of generic, abuse-prone medications which could have a detrimental effect on public health. Therefore, the FDA's encouragement to pharmaceutical companies urging them to produce and develop more abuse-deterrent opioid drugs must go hand-in-hand with insurance plan removal of "fail-first" requirements and other restrictions that induce riskier opioid consumption. Alternatively, it may be in the interest of society to restrict detailing promotion of opioid drugs and to encourage prescriber education about opioid medications through "academic detailing" where information diffuses through a channel that does not pose a potential conflict of interest.

3. ACCOUNTABLE CARE ORGANIZATIONS AND PHYSICIAN ANTIBIOTIC PRESCRIBING BEHAVIOR

with Sebastian Linde and Brandon Norton

3.1 Introduction

Many antibiotics prescriptions written by physicians in inpatient and outpatient settings are considered unnecessary (Griljalva et al., 2009). CDC studies estimate that about 30% of all antibiotic prescriptions in the US doctors' offices and emergency departments are written for infections that don't require antibiotic treatment.[1] These studies also suggest that even when antibiotics are required for infection treatment, the treatment courses are often longer than recommended (CDC, 2019). Such inappropriate antibiotic prescribing can lead to serious adverse side effects in patients and contribute to antibiotic resistance, which is both a growing public health threat and increases health care costs (Spellberg et al., 2008). The current literature primarily focuses on the effectiveness of hospital antimicrobial utilization improvement programs using data on individual facilities, specific settings, or specific conditions (Abuali et al., 2019; Andrajati et al., 2017; Ashworth et al., 2005; Barlam et al., 2015; Butler et al., 2012). However, little is known about the general driving factors behind physician-level antibiotic prescribing as well as potential peer effects. In this paper we quantify the causal spillover effect of joining an Accountable Care Organization (ACO) on antibiotic prescribing behavior.

ACOs are groups of health care providers that coordinate care for Medicare patients with the goal of achieving a higher standard of care as well as reduced costs of care. ACOs were designed to align the incentives of health providers with the goals of the overall Medicare system by exposing health providers to the costs of care. If ACOs achieve high levels of care and cost savings they capture a percentage of that savings as profit.

[1] Antibiotics only treat certain infections caused by bacteria, and do not work on viruses that cause colds, flu, and most cases of bronchitis. Antibiotics are usually not needed for common bacterial infections (https://www.cdc.gov/antibiotic-use/community/about/can-do.html).

However, some types of ACOs may face downside risk if they fail to achieve sufficient outcome scores.[2] Previous work suggests that ACOs have had some modest success in improving care and reducing spending (Kaufman et al., 2019; McWilliams et al., 2015). ACO membership could influence antibiotic prescribing in several ways. Since patient satisfaction scores are an explicit outcome for determining ACO effectiveness, a physician might increase prescribing after joining an ACO in order to improve patient satisfaction metrics. On the other hand, a desire to reduce costs might result in fewer prescriptions. There is little theoretical reason to expect either effect to dominate.

Naturally, a number of individual and institutional features may influence physicians antibiotic prescribing behavior, which we measure by the total number of antibiotic prescriptions written for Medicare Part D patients. Many of these features are observable. We divide these observable features in to four categories: physician characteristics, physician affiliations, patient characteristics, and volume.

There may also be unknown or unobserved characteristics that explain antibiotic prescription behavior such as the physician's own expectation of future resistance risk, their discount rate of that future risk, the patient's beliefs about their condition, the patient's insistence on receiving a prescription, etc. All of these can be contributors to a physician's likelihood of prescribing an antibiotic but cannot be observed.

In this paper we focus on identifying the spillover effects that physician ACO participation has on their antibiotic prescribing behavior. The identification of this effect is complicated by the treatment (ACO participation) not being randomly assigned to physicians, and as such, this presents a selection problem due to the choice to either receive the treatment or not. This decision about whether or not to become affiliated with an ACO may be driven by both the observable characteristics mentioned above (which we are able to adjust for) as well as by characteristics that are not observed by the econometrician but which may simultaneously affect antibiotic prescribing. In order to address these empirical challenges we employ a two-part structural model that accounts for both the decision to join an ACO and the effect that this has on the physician's subsequent antibiotic prescribing behavior.

[2]See https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/for-acos/index for more information.

To analyze this model we use three datasets: Medicare Part D claims, Medicare Part B claims, and Physician Compare.[3] These data allow us to control for many variables relating to patients and physicians.

We find that ACO affiliation helps reduce antibiotic prescribing by 23.9 prescriptions (about 23%) per year. The treatment effect is found to vary with specialty. Internal medicine physicians experience an average decrease of 19%, family and general practice physicians a decrease of 16%, and nurse practitioners a decrease of 12.5% in their antibiotic prescribing per year. In terms of selection into treatment, we show that failure to account for selection on physician unobservable characteristics results in an understating of the average treatment effects.

We contribute to a number of existing literatures. First, we contribute to the literature on antibiotic prescribing behavior and the impact of antibiotic resistance by showing one channel in which antibiotic prescribing could be reduced. Second, we contribute to the literature on the effectiveness of Accountable Care Organizations by showing a previously unknown, and beneficial, spillover effect of ACOs.

3.2 Model

To explain antibiotic prescribing behavior and isolate the effect of ACO membership we use a directed acyclical graphical model. Figure C.1 illustrates how observed and unobserved characteristics affect both membership in ACOs and antibiotic prescriptions. Our primary outcome of interest, *AB Claims*, is the total number of antibiotic prescriptions a physician writes for Part D patients. In this paper we do not differentiate between types of antibiotics, or attempt to determine if the prescription was inappropriate, as our goal is only to identify the causal effect of ACO participation on the overall volume of prescriptions. However, any reduction in antibiotic utilization as a result of ACO participation is likely to include a decrease in unnecessary prescribing given the sheer proportion of antibiotic overuse estimated by the literature. Furthermore, ACOs incentivize doctors to reduce unnecessary care while maintaining high healthcare quality standards.

[3]See section 3.3 for more details.

A physician is part of the treatment group if he or she is a member of an ACO at any point during a given year. Initially it is unclear what effect membership in an ACO will have on antibiotic prescribing behavior. There is little previous work on the influence of peers or group affiliations on antibiotic prescribing behavior. One exception is Charani et al. (2013), which found an existence of an "etiquette" on antibiotic prescribing within a practice group but that many physicians felt they had the autonomy to prescribe as they wished. However, the paper is limited to surveys of a small sample of physicians in only four hospitals and is not specific to ACOs. Additionally, their results do not predict the direction of the effect that being in a group practice would have on prescribing behavior. It is plausible that, if physicians care about future antibiotic resistance, there would be social pressure on ACO members to limit prescribing. Additionally, social pressure to reduce overall costs could limit unnecessary prescribing. However, there is a trade off between prescribing behavior and patient satisfaction if patients generally expect to receive a prescription when visiting the doctor (Ashworth et al., 2016). If patient satisfaction scores are more important to ACO members than antibiotic resistance then it is also plausible that ACO membership could increase antibiotic prescribing. Thus, both the direction and magnitude of the treatment effect is ultimately an empirical question.

The top row in Figure C.1 shows four categories of observable characteristics. The dashed black lines indicate that these observable characteristics are associated with both antibiotic prescribing and membership in ACOs. First, the volume of patients a physician sees will clearly influence the number of prescriptions he or she writes. Volume might also make a physician more attractive to an ACO since there is a higher potential for efficiency savings (and, thus, opportunity for profit) with more patients.

Second, we consider patient characteristics such as age, sex, income, etc. These will be described in detail in the next section. Some studies have found that patient race, sex, and concurrent conditions affect antibiotic prescribing (Gerber et al., 2013; Sun et al., 2006). Other studies have found the opposite, that many of these patient characteristics do not influence antibiotic utilization by doctors (Steinman et al., 2006).

Certain observable physician characteristics are also likely to have effects on prescription behavior and ACO membership. These include primary specialization, physician sex, strength of the medical school the physician attended, and use of electronic health records.

Previous work has shown that physician specialty and sex can affect antibiotic prescribing (Steinman et al., 2006; Sun et al., 2006; Wang et al., 2009). The physical location of the physician's office also matters (Steinman et al., 2006; Sun et al., 2006; Wang et al., 2009). We control for the type of commuting area the provider is located in (urban or rural), as well as their hospital referral region.

Last, to help ensure we isolate the effect of ACO participation rather than the general attitude of the physician to collaboration and group practice, we account for several group practice and affiliation variables. These include the number of practices the physician belongs to, the number of hospital affiliations, and the total number of members in the physician's practices. Although no papers have specifically examined the relationship between ACO membership and antibiotic prescribing, several have looked at some aspect of group practice. Parente et al. (2017) found a difference between prescribing in teaching versus non-teaching hospitals. Steinman et al. (2006) found an effect for membership in a Health Maintenance Organization (HMO). Charani et al. (2013) explains prescribing etiquette for a small sample of hospitals but makes no quantitative prediction of the effect on antibiotic prescribing.

Even with many observed variables, simply controlling for them and running a multivariate regression of ACO membership on antibiotic prescribing is problematic because ACO membership is not randomly assigned. Physicians self-select into ACO membership and there are at least some potential unobserved characteristics that could be correlated with both ACO membership and antibiotic prescribing.[4] We show this graphically in Figure C.1 by the red dashed lines. This endogeneity problem means Ordinary Least Squares coefficient estimates will be biased. We describe how we test for and solve this problem using a two-part structural selection model in the Statistical Analysis section. Once we account for this issue we can measure the actual treatment effect of ACO membership, represented by the solid blue line in Figure C.1.

[4]For example, the extent to which a physician values patient satisfaction could influence their willingness to provide an unnecessary antibiotic as well as how attractive they would be as a potential ACO member.

3.3 Methods

3.3.1 Study Population and Data Sources

We analyze Medicare Part D antibiotic claims for a panel of providers for years 2016 and 2017. Three data sources are utilized - Medicare Part D, Medicare Part B (also referred to as Physician and Other Supplier), and Physician Compare datasets.

The antibiotic claims and other prescription data come from Part D Prescriber Public Use File (PUF). The primary data source for the Part D PUF is the Centers for Medicare & Medicaid (CMS) Chronic Conditions Data Warehouse, which contains Medicare Part D prescription drug events (PDEs) of Medicare beneficiaries with a Part D prescription drug plan. The data contains information on drug utilization and costs for beneficiaries enrolled in the Medicare Part D prescription drug program.[5] Provider demographics is based on information extracted from National Plan Provider Enumeration System (NPPES).

The Physician and Other Supplier PUF contains final-action claims information on Medicare Part B services and procedures provided to Medicare beneficiaries enrolled in the fee-for-services program. Part B covers physician office visits, lab and diagnostic tests, medical equipment, ambulance, and other outpatient services.

Created by CMS in Dec 2010 as a requirement of the Affordable Care Act (ACA) of 2010, the Physician Compare dataset contains up-to-date information on physicians and groups enrolled in Medicare, including performance and quality measures. It was created to help patients make informed choices about their medical care. It contains data on innovative model participation (ACOs), Electronic Health Record Technology participation, performance information, and patient survey scores.

Our data sources identify the providers by their National Provider Identifier (NPI). We use physician NPI and year to match physicians in the three datasets. After dropping non-US based physicians, the final sample for 2016-2017 consists of 1,120,690 observations (a total of 645,620 physicians, most of which are in both years of the data). About one third of the physicians belonged to an ACO in this time frame. Since the majority of

[5]This makes up about 70% of all Medicare beneficiaries, of which about two-thirds are enrolled in stand-alone Prescription Drug Plans and one-third enrolled in Medicare Advantage Prescription Drug Plans.

non-pediatric primary care doctors (93%) accept Medicare,[6] our sample captures most physicians practicing in the US (Boccuti et al., 2015).

3.3.2 Study Variables

Antibiotic Prescribing and Accountable Care Organizations

We use Medicare Part D yearly antibiotic claims for each physician as a measure of antibiotic prescribing. Since older adults utilize about 50% more antibiotics per person than younger adults and have the highest risk for antibiotic-related adverse outcomes, this population is particularly important to examine (Olesen et al., 2018). Because physician-level claims are suppressed if they fall in the interval 1-10, we impute the mean value and conduct a robustness test that accounts for censoring.[7]

The main explanatory variable of interest is the physician's ACO participation. We utilize an indicator variable that is equal to one if the provider belongs to an ACO in a given year. Our ACO measure comes from the Physician Compare dataset and accounts for participation in any of the ACO programs offered by Medicare, including Medicare Shared Savings Program, ACO Investment Model, Advance Payment ACO Model, Comprehensive ESRD Care Initiative, Next Generation ACO Model, Pioneer ACO Model, and Vermont All-Payer ACO Model.[8]

Provider Characteristics and Affiliations

In order to account for group- and peer-level factors that affect prescribing behavior and probability of selection into ACOs, we include as controls the number of practices that the physician is a part of, the total number of group members across those groups, as well as the number of hospitals that the physician is affiliated with.

[6]This number is comparable to the proportion of physicians that accept private insurance, which is 94%.

[7]Within the main analysis we impute the mean value for any censored outcome variable. However, to assesses the robustness of this approach we also estimate a maximum likelihood model that allows us to directly account for censoring within the specification of the likelihood function (a la Wooldridge (2010)). Results from the maximum likelihood model are provided within Table C.7, along with the full-sample results reported within Table C.3. Comparing the results we note that that they are almost identical, indicating no meaningful difference between our imputation approach and the maximum likelihood approach.

[8]For more information on various ACO models, see https://innovation.cms.gov/innovation-models/aco.

Because doctors who utilize electronic health records (EHRs) are potentially more aware of patients' overall healthcare utilization patterns and prescription history, as well as have better access to diagnostic test results, such physicians may also prescribe antibiotics differently compared to those who do not use EHRs. Furthermore, ACO participation incentivizes coordination to deliver quality care to patients, which requires extensive use of technology such as referral systems and EHRs. We include a dummy variable for whether the physician uses EHRs to account for technological proficiency. Because attending a top medical school is a proxy for a physician's training quality, it may play a role in prescribing habits and coordination ability. An indicator variable for whether the physician attended a top 25 medical school is included in the model to control for medical education quality.[9] An indicator variable for whether the doctor is a female accounts for any gender differences in prescribing patterns and coordination skills. Finally, physician specialty fixed effects control for differences in antibiotic prescribing across practice types, as well as variation in how specialties deal with preventative care, coordination, and underlying services, which may also affect the probability of joining an ACO.

Patient Characteristics and Other Covariates

Since the underlying patient population's health and socioeconomic status may play an important role in the provider's prescribing patterns and the decision to join an ACO, our model includes the physician's part B beneficiaries' average age and average risk score.[10]

Previous literature suggests that time- and patient-pressure may be an important determinant in how physicians prescribe antibiotics. Some reasons for unnecessary antibiotic prescriptions include pressure to meet patients' expectations, fear of complications, and fatigue (Feller, 2019). Because these factors are likely to increase with the volume of patients and may affect the provider's decision to join an ACO, we include as covariates the

[9] Our ranking is based on the U.S. News annual rankings of medical schools across research and primary care.

[10] CMS developed a risk-adjustment model that uses HCCs (Hierarchical Condition Categories) to assign risk scores. Risk scores are based on a beneficiary's age and sex; whether the beneficiary is eligible for Medicaid, first qualified for Medicare on the basis of disability, or lives in an institution; and the beneficiary's diagnoses from the previous year. The scores estimate how beneficiaries' fee-for-services spending will compare to the overall average for the entire Medicare population. Beneficiaries with scores greater than the average risk score are expected to have above-average spending, and vice versa.

total number and charges for Part B physician services, as well as the number of patients receiving them. The physician's prescribing preferences are captured by the number and the cost of part D claims.

To account for geographic and population density factors that may affect both ACO participation and prescribing practices, our model includes the Hospital Referral Region (HRR) and Rural-Urban Commuting Area (RUCA) fixed effects. HRRs are 306 geographical units for tertiary care for Medicare beneficiaries. Each HRR is required to have a minimum population of 120,000, have the largest proportion of major cardiovascular procedures, and the residents of each HRR must receive at least 65% of their hospitalizations within that HRR.[11] The RUCA codes classify U.S. census tracts using population density, urbanization, and commuting.[12] We utilize 10 primary whole-number codes that delineate metropolitan, micropolitan, small town, and rural commuting areas.[13]

3.3.3 Data Descriptives

Table C.1 presents summary statistics for the full sample of physicians separated into ACO and non-ACO categories.[14] In the full sample of physicians, about one-third belong to an ACO. ACO affiliated doctors tend to have fewer antibiotic claims. They have more affiliations, are more likely to graduate from a top medical school, more likely to use electronic health records, and are more likely to be a female. Additionally, both the patient populations as well as the services-related characteristics of ACO and non-ACO affiliated doctors are significantly different. Such differences highlight the importance of controlling for the observable characteristics when estimating the effect of ACO participation on prescribing behavior.

Table C.2 contains summary statistics for three select specialties - internal medicine, family and general practice, and nurse practitioners. Together these specialties account for 67.2% of all antibiotic claims. About one-third of providers in each specialty category are

[11] See https://www.dartmouthatlas.org for more details on HRR.

[12] See https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes.aspx for details on RUCA codes.

[13] The secondary non-whole number codes, which represent further subdivisions, were rounded to the nearest whole number for simplicity.

[14] Additional summary statistics for the full sample of providers, as well as the sample of physicians who prescribed antibiotics, can be found in Appendix C Table C.5.

affiliated with an ACO, and, with the exception of nurse practitioners, tend to prescribe more antibiotics compared to the average physician in the full sample.

3.3.4 Statistical Analysis

In order to estimate the spillover effects that ACO affiliation has on physicians' antibiotic prescribing behavior we employ a potential outcomes framework, a la Rosenbaum and Rubin (1983). Let $AB_{it}(ACO_{it})$ denote the antibiotic prescribing by physician i, in period t, where $ACO_{it} \in \{0, 1\}$ is an indicator for whether physician i is affiliated with an ACO, then the sought average treatment effect is given by

$$\tau = \mathbb{E}\left[AB_{it}(1) - AB_{it}(0)\right],$$

where $AB_{it}(1)$ denotes the antibiotic prescribing of physician i if they are treated ($ACO_{it} = 1$), and $AB_{it}(0)$ denotes the counterfactual outcome for physician i if they are untreated ($ACO_{it} = 0$). A problem confronting the estimation of the average treatment effect (τ) in our setting is that physicians self-select into treatment, that is, we do not have random assignment of our treatment (ACO affiliation). To address this we draw on our behavior model (from Section 2) to help inform our set of control variables, x_{it}, which account for: (i) physician characteristics, (ii) physician affiliations, (iii) physician quantity of services, and (iv) patient characteristics. However, as also noted within our behavioral model, physicians may self-select into treatment based on unobservable characteristics that can also influence their antibiotic prescribing behavior, causing our treatment to be endogenous.

In order to resolve this endogeneity concern we use a two-part structural selection model that allows us to control for selection into treatment based on both observable and unobservable physician characteristics. Here, our outcome regression of interest is given by,

$$AB_{it} = \alpha + x_{it}\beta + \tau ACO_{it} + \varphi_t + \lambda_s + \nu_h + \kappa_r + \epsilon_{it}, \tag{3.1}$$

where our observed treatment (ACO_{it}) depends on the latent utility U_{it}^* that physician i gets from selecting into treatment, that is,

$$ACO_{it} = \begin{cases} 1 & \text{if } U_{it}^* = \delta + w_{it}\gamma + \eta_t + \psi_s + \chi_h + \upsilon_r + u_{it} > 0 \\ 0 & \text{if } U_{it}^* = \delta + w_{it}\gamma + \eta_t + \psi_s + \chi_h + \upsilon_r + u_{it} \leq 0 \end{cases} \tag{3.2}$$

In Equations (3.1) and (3.2) φ_t and η_t denote time fixed effects, λ_s and ψ_s capture specialty fixed effects, ν_h and χ_h control for geographic variation across hospital referral regions, κ_r and υ_r are fixed effects for how urban/rural a given area is, and the residuals ϵ_{it} and u_{it} are bivariate normal with mean zero and a covariance matrix structure given by:

$$\begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}$$

We estimate this structural model using the Heckman (1976, 1978) two-step procedure as outlined by Maddala (1986). In the first step we obtain probit estimates for the parameters $(\hat{\delta}, \hat{\gamma}, \hat{\eta_t}, \hat{\psi_s}, \hat{\chi_h}, \hat{\upsilon_r})$ from Equation (3.2), using an exclusion restriction for experience such that $w_i = [x_{it}, experience_{it}]$.[15] Using these estimates we compute the hazard rate, h_{it}, for each observation as

$$h_{it} = \begin{cases} \phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta_t} + \hat{\psi_s} + \hat{\chi_h} + \hat{\upsilon_r}) / \Phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta_t} + \hat{\psi_s} + \hat{\chi_h} + \hat{\upsilon_r}) & \text{if } ACO_{it} = 1 \\ -\phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta_t} + \hat{\psi_s} + \hat{\chi_h} + \hat{\upsilon_r}) / \left(1 - \Phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta_t} + \hat{\psi_s} + \hat{\chi_h} + \hat{\upsilon_r})\right) & \text{if } ACO_{it} = 0 \end{cases},$$

and, using the hazard rate, we estimate the revised outcome equation,

$$AB_{it} = \alpha + x_{it}\beta + \tau ACO_{it} + \rho\sigma h_{it} + \varphi_t + \lambda_s + \nu_h + \kappa_r + \epsilon_{it}, \tag{3.3}$$

within the second and final step. As noted, the important benefit of this approach is that it allows us to control for potential selection on unobservables in order to resolve our treatment endogeneity concern.[16]

[15] Previous work has found that physician experience is uncorrelated with antibiotic prescribing (Barlam et al., 2015). Moreover, Donohue et al. (2018) impose similar exclusion restrictions pertaining to physician age within their study of physician drug adoption.

[16] Another benefit of this approach is that it allows us to directly test for treatment endogeneity within our final regression, Equation (3.3), by seeing if the estimate $\hat{\rho\sigma}$ is significant.

As such, our identification strategy for obtaining our estimates rests on the conditional independence assumption that treatment is assigned as good as random once we control for selection on observables, x_{it}, the unobservables (captured by the hazard h_{it}), potential time effects, φ_t, specialty effects,λ_s, hospital referral region effects, ν_h and how rural the region is, κ_r. Stated formally, our identification rests on:

$$\{AB(0), AB(1)\} \perp ACO_{it} \mid x_{it}, h_{it}, \varphi_t, \lambda_s, \nu_h, \kappa_r.$$

3.4 Results

3.4.1 Ordinary Least Squares Regression Results

Table (C.3) displays the coefficient estimates obtained by Ordinary Least Squares (OLS) regression. Columns 1 and 2 present the estimated effects of ACO participation on antibiotic claims for the full sample of physicians, and columns 3 and 4 effects are estimated for the physicians who had more than zero antibiotic claims for years 2016 and 2017.

Column 1 results indicate that physicians who participate in ACOs have on average 2.6 fewer yearly antibiotic claims than non-ACO providers[17], which represents a 3.5% decrease from the average antibiotic prescribing for the full sample. However, because antibiotic prescribing is likely to vary by specialty, we expect the effect of ACO to be heterogeneous across different types of practices. In column 2 we include interacted specialty by ACO dummy variables for specialties with the highest proportion of antibiotic prescribing - internal medicine physicians, doctors who are in general/family practice, and nurse practitioners. Together, these specialties account for 67.2% of all antibiotic claims. The estimates suggest the presence of heterogeneity in how ACO participation affects prescribing across provider types, with all ACO-related coefficients being significant at 1% significance level. Internal medicine physicians who are part of an ACO have 13.2 fewer antibiotic claims relative to their non-ACO counterparts.[18] Given that internal medicine providers write 131.51 antibiotic prescriptions on average, the estimated effect for this specialty corresponds to about a 10% decline in claims from ACO membership.

[17] Significant at 1% level.
[18] $1.281 - 14.53 = -13.249$.

Family and general practice physicians have 11.1 fewer antibiotic claims compared to the same type of doctors who are not participating in ACOs - a 7% decrease from the average for that specialty. The ACO-participating nurse practitioners, on the other hand, appear to have 5.7 more antibiotic claims than non-ACO ones, which is about a 9% increase from the mean. The ACO coefficient is positive and significant, indicating that providers in specialties other than ones accounted for by the interaction terms may experience an increase in antibiotic prescribing of about 1.3 claims due to ACO participation.

The ACO coefficient estimate in column 3 indicates that the effect of ACO participation on antibiotic claims may be greater for the sample of physicians who prescribed antibiotics in 2016 and 2017. ACO-participating providers have 4.8 less yearly antibiotic claims than non-ACO physicians, which is significant at 1%-level and represents a 4.6% decline from the average number of claims for this sample of prescribers. When we include the specialty interaction terms in column 4, the ACO coefficient remains negative (although not significant) indicating that ACO participation may lower antibiotic prescriptions for the remaining specialties, although substantial amount of heterogeneity may be present for the remaining specialties. The results show that physicians practicing internal medicine reduce their yearly antibiotic claims by 12.1, or 8.4% of the sample mean, when they join an ACO. While family and general practitioners decrease antibiotic prescribing by 10.6 claims per year, which corresponds to 6.6% of the sample average, the nurse practitioners appear to increase their antibiotic prescribing by 4.7 claims, or 5.5% of the mean.[19]

3.4.2 Structural Selection Model Estimation Results

A potential concern with these regression results is that latent features that drive physicians' ACO participation decision also influence their antibiotic prescribing behavior.

[19] We also conduct the analysis using the propensity score matching approach (see Appendix C for results). Figure C.2 shows the propensity score distributions for the treated (dark-gray) and the untreated (light-grey).These propensity scores are based on Probit regression results that use the same controls as our other results within the paper. This shows that we have common support for the propensity scores. In terms of establishing balance pre- and post-propensity score matching, Figures C.3 and C.4, show that we have good balance for majority of the controls post matching. Lastly, Table C.10 presents average treatment effect on treated results from the propensity score matching. Column (1) shows the ATT results for the full sample, while column (2) presents the results for the prescribe sub-sample. In terms of magnitudes, these are found to be similar to the estimates obtained with OLS.

For example, if a physician selects into treatment (ACO affiliation) on the basis of expected shared savings program savings, or on being less risk averse, then one might anticipate that our regression results in Table C.3 are upward biased. To account for the potential endogeneity of ACO affiliation, Table C.4 presents two-step regression results that control for selection on unobservables. Columns (1) and (2) present results for the full sample, while columns (3) and (4) present results for the active antibiotic prescriber subsample.

Looking at the full sample in column (1) first, we see that ACO affiliation is associated with an average 18.2 prescription reduction in antibiotic prescribing, which corresponds to about a 25% reduction. Column (2) further showcases the heterogeneity of these treatment effects. For physicians with a primary specialty in internal medicine, ACO affiliation is associated with a 24.5 antibiotic prescription (or 18.6%) reduction, while the effect for physicians with a primary specialty of family or general practice is a 22.3 prescription (or 14.5%) reduction. Looking at the treatment effect on nurse practitioners we find an overall prescribing reduction of 5.7 antibiotic prescriptions (or about a 9% reduction).

Conditioning on only prescribers gives qualitatively similar results. Firstly, as seen in column (3), the overall average treatment increases in its magnitude to a 23.9 antibiotic prescription (or about 23%) reduction. Column (4) indicates that when conditioning on prescribers, internal medicine physicians experience an average 27.2 antibiotic prescription (about 19%) reduction, while family or general practice physicians have an average 25.6 antibiotic prescription (or 16%) decrease. For nurse practitioners, the average treatment effect is a reduction of 10.5 prescriptions, a 12.5% fall.

Lastly, in comparing the two-step results to our naive regression results (those in Table C.3) we see that the naive regression results indeed appear to be subject to considerable upward bias. This is further supported by the observation that our $\widehat{\rho\sigma}$ estimate is positive and statistically significant across all specifications within Table C.4 - indicating that ACO affiliation is endogenous, and that accounting for selection on unobservables is appropriate.

3.5 Discussion

In this paper we show the effect of several observable characteristics on physician antibiotic prescribing while correcting for the endogeneity of unobserved characteristics.

We confirm studies such as Gerber et al. (2013) and Sun et al. (2006) that find patient characteristics like age, sex, and concurrent conditions matter. We also show that patient income is an important aspect of antibiotic prescribing. We also confirm the many papers that show physician characteristics like specialty, geographical location, and sex matter. Beyond these, we also find that the rank of the physician's medical school and the use of electronic health records can be important determinants of antibiotic prescription behavior. Our paper is the first to quantify organizational peer effects on antibiotic prescribing behavior. We show how the number of hospital affiliations, number of practices, and number of practice members affect antibiotic prescribing. Most importantly, we are the first to show there is an effect, and quantify that effect, of ACO membership on antibiotic prescribing behavior.

As reported in the previous section, our average treatment effect shows ACO membership can reduce the number of antibiotic prescriptions by roughly a quarter. Since patient satisfaction is also an important component of measuring ACO effectiveness, it is likely that most of the reduction in prescribing is for unnecessary antibiotics. Thus, incentivising ACO membership might provide an additional channel to reduce antibiotic resistance beyond traditional antibiotic stewardship programs. Since peer effects alone seem capable of significantly reducing antibiotic prescribing, policy makers might consider using an antibiotic stewardship component in measuring ACO performance. Rewarding low unnecessary antibiotic prescribing with additional shared savings could increase the antibiotic resistance benefit beyond what we have shown in this study.

An additional finding of our study is that average treatment effects due to ACO participation on antibiotic prescribing are heterogeneous across different medical providers and physician specialties. In particular, when conditioning on active prescribers, we observe an average 19% reduction on antibiotic prescribing for physicians with an internal medicine specialty, which is higher than that measured for physicians with a family and general practice specialty, who had an average 16% reduction, and that for nurse practitioners, who on average experience a 12.5% reduction. These differences in the relative treatment effects are particularly interesting when noting that we control for factors related to physician affiliations, physicians characteristics, patient characteristics, quantity (or volume) of services rendered, along with any systematic antibiotic prescribing behav-

ior that may stem form the providers primary specialty, time, geography and selection into treatment. As such, this appears to be an interesting avenue for future work that may seek to further explore these heterogeneities across more specialties, and to further probe the potential sources of these heterogeneous treatment responses across specialties.

Our results present the first evidence of substantial positive spillover effects of ACO participation on antibiotic prescribing. While many papers have looked at the beneficial effects of ACO membership, their estimates may understate the societal benefits of ACOs given that indirect effects, such as lower antibiotic prescribing, are unaccounted for. Therefore, our findings have important implications for healthcare policy. Given the increasing importance of containing the growth of antibiotic resistance, policymakers have focused on reducing unnecessary antimicrobial prescriptions primarily through the introduction of antibiotic stewardship programs. However, our results indicate that antibiotic prescribing can also be reduced through policies that encourage ACO participation and potentially other actions that encourage quality care and efficiency in the delivery of medical services through increased physician coordination and accountability. In addition to improving healthcare quality and reducing medical costs, ACOs may play a role in enhancing patient and public health safety through better antibiotic utilization.

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A. APPENDIX: INERTIA AND SWITCHING IN HEALTH INSURANCE PLANS

Table A.1.: Summary Statistics

	Mean	Std. Dev.
shock	0.053	0.224
salaried	0.874	1.413
age	51.711	10.537
child19	0.469	0.890
spouse	0.449	0.497
claims	23.852	26.648
RxOOP	457.234	771.707
N	*21,675*	

Table A.2.: Family Distribution Across New Plans

	HEALTH	HSA1	HSA2	*Total*
All families				
2014	1,144	2,224	967	4,335
2015	1,115	2,210	1,010	4,335
2016	1,059	2,159	1,117	4,335
Total	3,318	6,593	3,094	13,005
Families with shocks				
2014	56	121	25	202
2015	57	96	34	187
2016	34	65	23	122
Total	147	282	82	511

Table A.3.: Number and Types of Shocks

	2014	**2015**
Cancer	95	83
Asthma	69	66
Chronic kidney disease	23	16
Type 1 diabetes	6	10
Brain injury	13	12
Heart attack	0	1
Heart failure	6	10
Total	212	198

Table A.4.: University Plan Comparisons, 2014-2016

	HSA	Deductible In-Net	Coinsurance In-Net	OOP Max In-Net	Premium ($< \$44,000$)	Premium ($> \$44,000$)	University HSA Contribution
Family Coverage							
HEALTH	No	\$1,500	80/20	\$4,800	\$1,345[a] \$2,828[b] \$3,834[c]	\$2,693 \$4,513 \$6,117	NA
HSA1	Yes	\$3,500	80/20	\$7,000	\$321 \$890 \$1,206	\$895 \$1,606 \$2,178	\$1,300
HSA2	Yes	\$5,000	75/25	\$10,000	\$37 \$204 \$241	\$276 \$833 \$1,129	\$1,300
Single Coverage							
HEALTH	No	\$750	80/20	\$2,400	\$747	\$1,496	NA
HSA1	Yes	\$1,750	80/20	\$3,500	\$178	\$497	\$1,300
HSA2	Yes	\$2,500	75/25	\$5,000	\$0	\$0	\$1,300

a. Employee & children
b. Employee & spouse
c. Employee & family

Table A.5.: Probability of Being in a New Plan

	HEALTH_t	HSA1_t	HSA2_t
$shock_{t-1}$	0.0355	0.0855*	0.0155
	(0.0235)	(0.0344)	(0.0343)
$year2015_{t-1}$	0.00483	-0.0519*	0.0522*
	(0.0189)	(0.0214)	(0.0260)
$HEALTH_{t-1}$	0.632***		-0.0172
	(0.0730)		(0.0794)
$HEALTHshock_{t-1}$	-0.137**		0.0151
	(0.0457)		(0.0420)
$HSA2_{t-1}$	0.0320	0.122	0.531***
	(0.0281)	(0.103)	(0.0543)
$HSA2shock_{t-1}$	0.00303	-0.363***	0.206+
	(0.0576)	(0.103)	(0.105)
$salaried_{t-1}$	0.00137	-0.0295+	0.0315
	(0.0218)	(0.0163)	(0.0317)
age_{t-1}	-0.0203	0.0583*	-0.0419
	(0.0247)	(0.0244)	(0.0322)
$child19_{t-1}$	-0.202	0.381**	-0.341
	(0.144)	(0.142)	(0.220)
$spouse_{t-1}$	-0.180	0.0648	0.347
	(0.324)	(0.157)	(0.469)
$claims_{t-1}$	0.000944+	-0.000777	-0.000603
	(0.000524)	(0.000719)	(0.000565)
$RxOOP_{t-1}$	0.0000119	0.00000182	-0.0000108
	(0.0000159)	(0.0000243)	(0.0000339)
$HSA1_{t-1}$		0.705***	
		(0.0931)	
$HSA1shock_{t-1}$		-0.139*	
		(0.0550)	
constant	1.278	-3.055*	2.277
	(1.215)	(1.338)	(1.590)
Hansen J	0.62	0.30	0.07
N	8670	8670	8670

System GMM estimation. Standard errors in parentheses

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B. APPENDIX: PHARMACEUTICAL OPIOID MARKETING AND PHYSICIAN PRESCRIBING BEHAVIOR

Table B.1.: Patented Prescription Opioids (2014-2017)

Name	**Firm**	**ADF**
Arymo ER	Egalet	yes
Butrans	Purdue Pharma	-
Dilaudid	Purdue Pharma	-
Hysingla ER	Purdue Pharma	yes
OxyContin	Purdue Pharma	yes
Exalgo	Mallincrodt	-
Xartemis	Mallincrodt	-
Abstral	Galena Biopharma/Sentynl	-
Subsys	Insys Therapeutics	-
Conzip	Vertical Pharma	-
Fentora	Teva Pharma	-
Lazanda	Depomed	-
Nucynta	Depomed/Janssen	-
Nucynta ER	Depomed/Janssen	-
Belbuca	Endo Pharma	-
Opana	Endo Pharma	-
Opana ER	Endo Pharma	-
Avinza	Pfizer	-
Embeda	Pfizer	yes
Oxecta	Pfizer	-
Zohydro ER	Pernix/Zogenix	-
Xtampza ER	Collegium Pharma	yes
Morphabond ER	Daiichi Sankyo	yes

Table B.2.: Opioid Interactions by Nature of Interaction (2014-2017)

Nature of Interaction	**Total Number ($ Value)**	**Average Per Doctor**
Total Interactions	565,892 ($41.9 Million)	3.19 ($236.25)
Food & Beverage	530,799 ($8.56 Million)	3.00 ($48.29)
Faculty/Speaker Services	15,551 ($26.5 Million)	0.09 ($149.36)
Continuing Education Services	4 ($9,000)	0.00002 ($0.05)
Consulting	945 ($2.5 Million)	0.005 ($14.10)
Education	9,053 ($184,301)	0.05 ($1.04)
Travel & Lodging	8,843 ($2.85 Million)	0.05 ($16.06)
Gift	38 ($7,508)	0.0002 ($0.04)
Honoraria	659 ($1.3 Million)	0.004 ($7.31)

Table B.3.: Summary Statistics (2014-2017)

	All	**Ever Interacted**
Covariates:		
Patented Interactions	0.30 (3.30)	3.19 (10.57)
ADF-only interactions	0.09 (1.34)	0.97 (4.41)
ADF+nonADF interactions	0.07 (0.71)	0.80 (2.23)
Non-ADF interactions	0.14 (2.06)	1.43 (6.66)
Patented-only interactions	0.30 (3.28)	3.18 (10.50)
Patented+Generic interactions	0.001 (0.08)	0.01 (0.26)
Generic interactions	0.003 (0.15)	0.03 (0.45)
Non-opioid claims	2,096.88 (3870.14)	5,519.93 (6908.13)
Number of physicians in group	406.94 (950.72)	140.29 (362.04)
Beneficiaries	203.54 (218.92)	369.96 (277.54)
Beneficiaries over age 65	196.84 (205.94)	294.83 (238.31)
Low-income subsidy claims	954.17 (2538.95)	2,701.92 (5021.23)
Female beneficiaries	118.14 (131.38)	223.32 (170.07)
Black beneficiaries	14.52 (47.00)	29.36 (71.97)
Dual beneficiaries	53.95 (83.27)	103.46 (121.07)
Other variables:		
Patented opioid claims	2.66 (21.71)	17.66 (61.94)
ADF opioid claims	2.00 (15.15)	12.31 (41.85)
Non-ADF opioid claims	0.66 (9.04)	5.35 (27.09)
Generic opioid claims	100.20 (323.47)	463.92 (815.42)
Opioid payments total ($)	22.34 (1108.15)	236.24 (3637.84)
Observations	2,067,806	177,227
Number of physicians	663,922	48,276

Sample means are reported for years 2014-2017, with standard deviations in parentheses. For some variations, number of observations may be lower due to missing information.

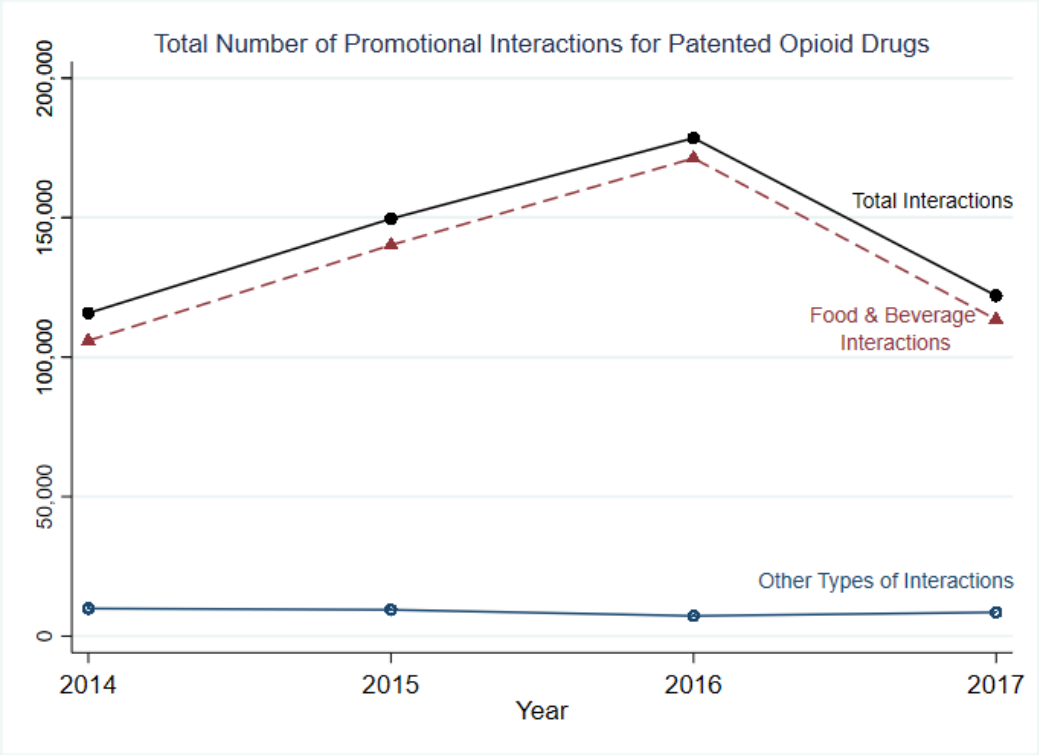

Figure B.1.: Total Number of Promotional Interactions for Patented Opioid Drugs

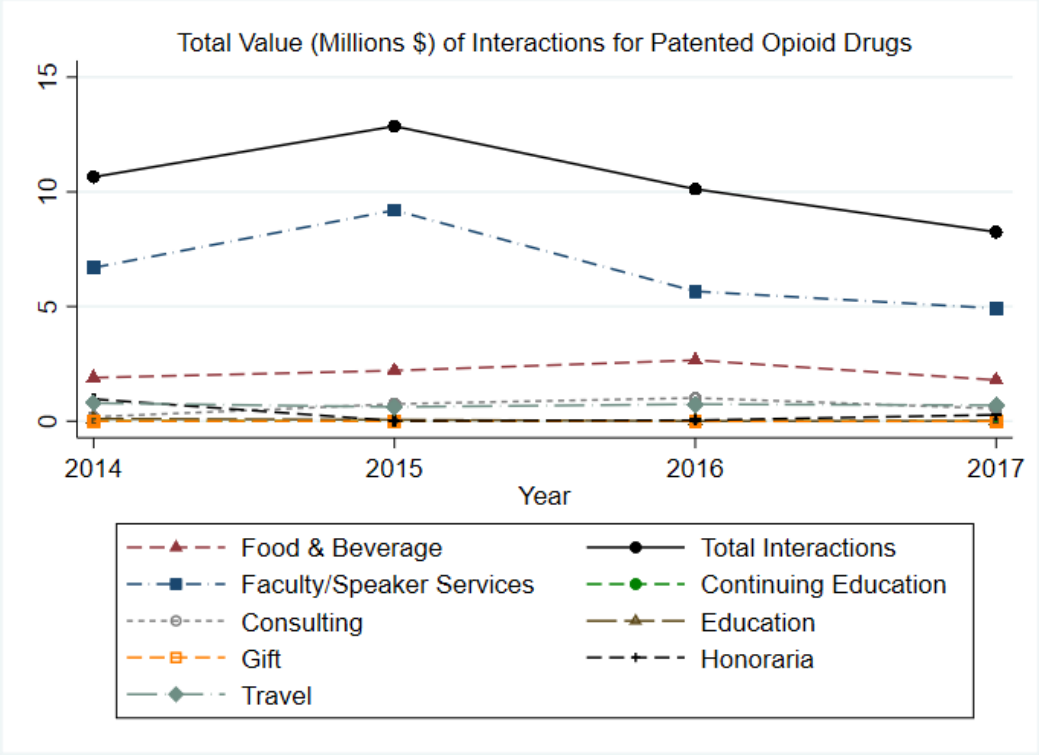

Figure B.2.: Total Value of Interactions for Patented Opioid Drugs

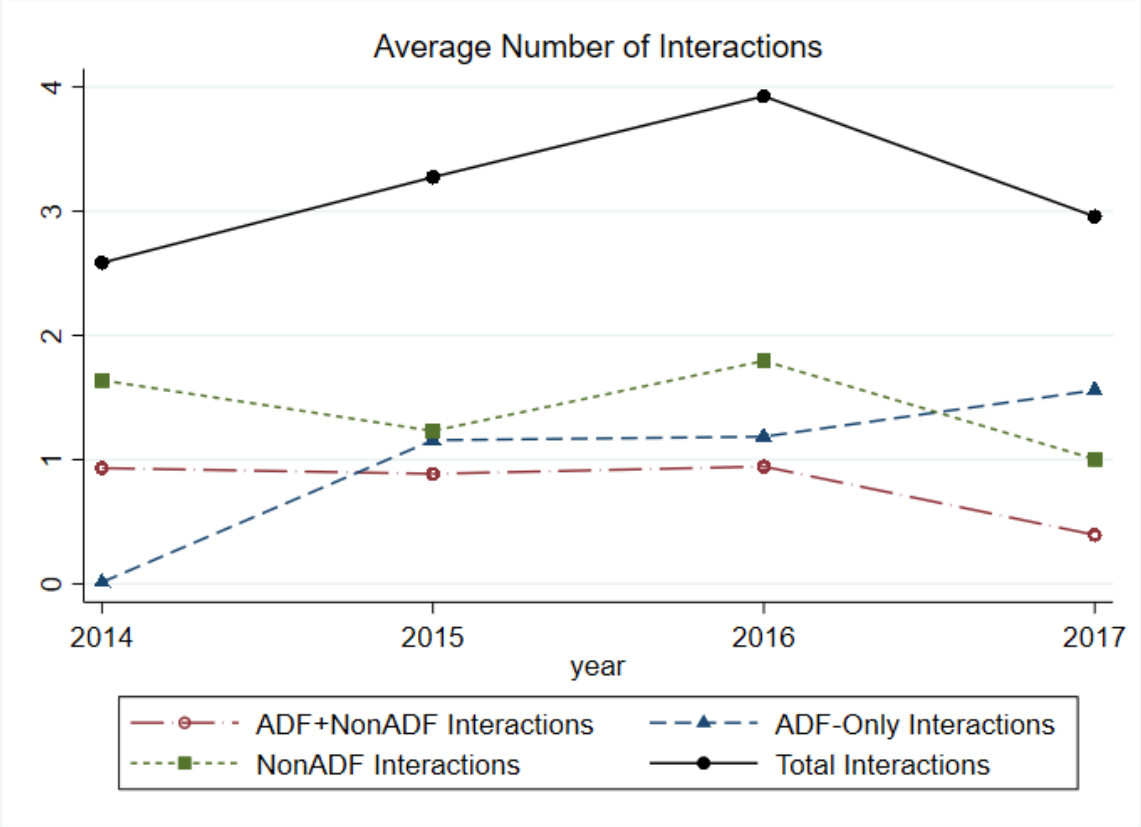

Figure B.3.: Average Number of Interactions

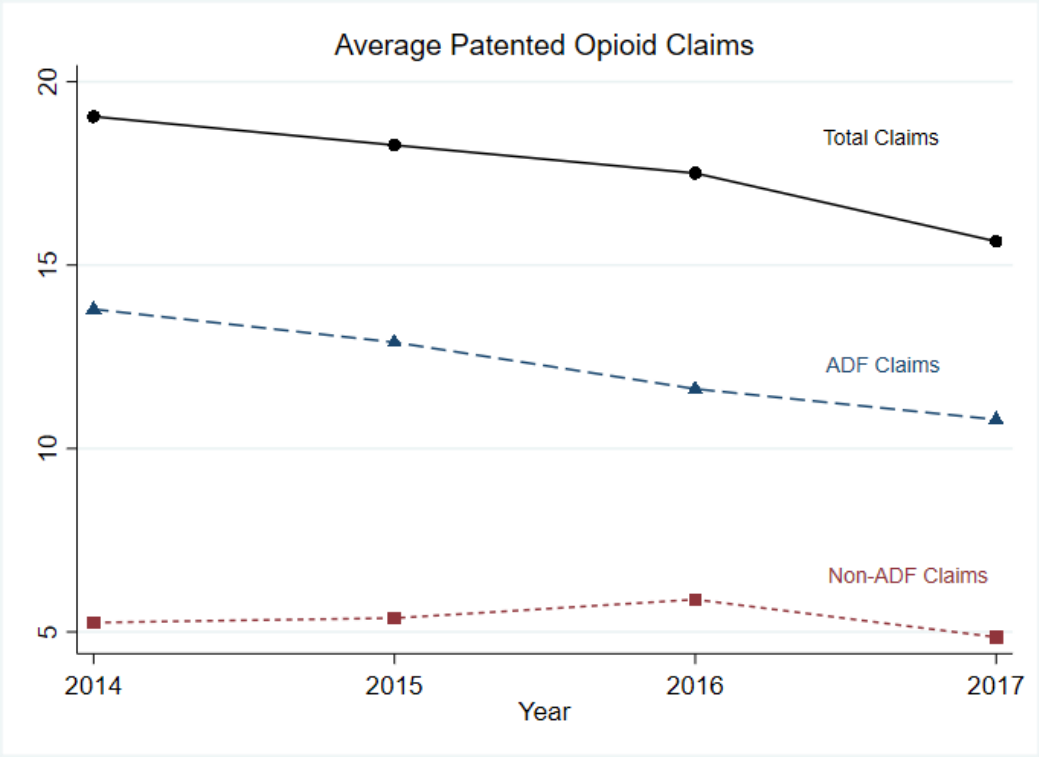

Figure B.4.: Average Patented Opioid Claims

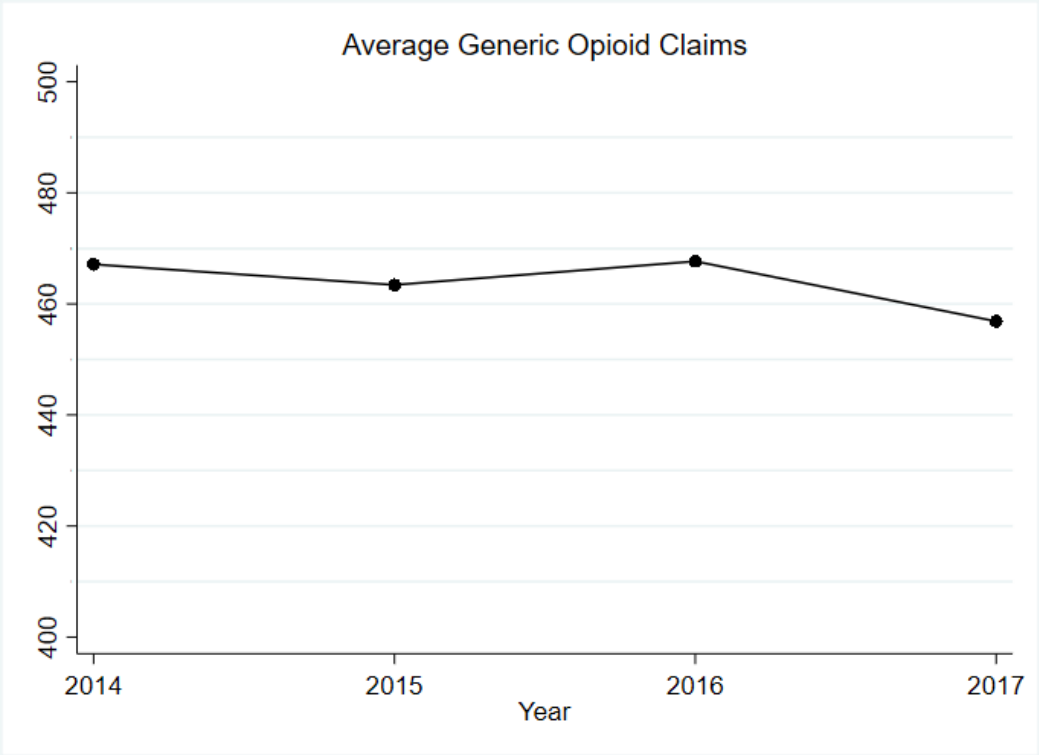

Figure B.5.: Average Generic Opioid Claims

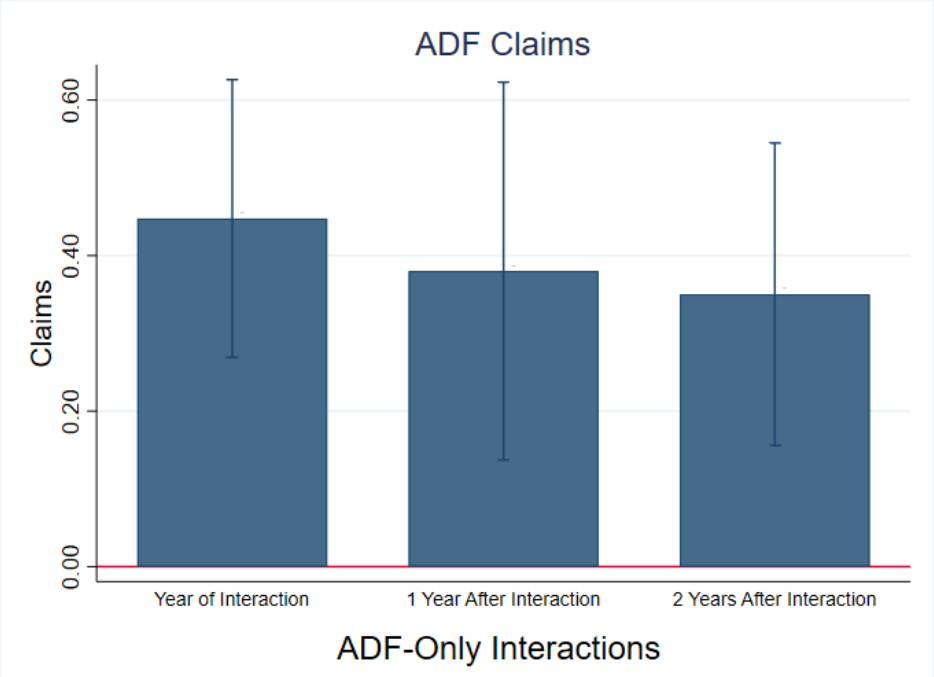

Figure B.6.: Effect of ADF-Only Interactions on ADF Claims

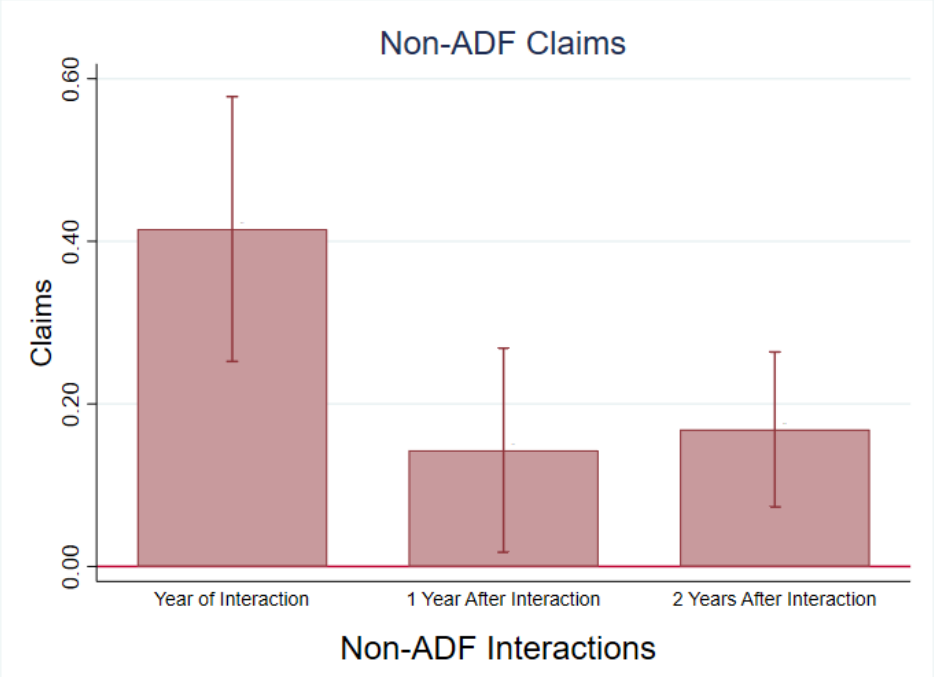

Figure B.7.: Effect of Non-ADF Interactions on Non-ADF Claims

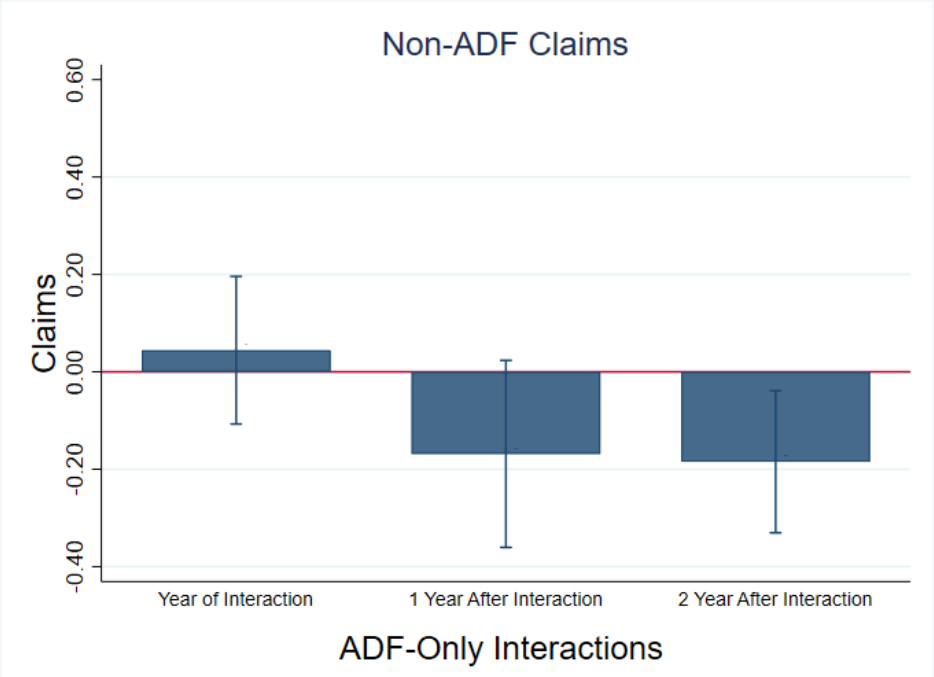

Figure B.8.: Effect of ADF-Only Interactions on Non-ADF Claims

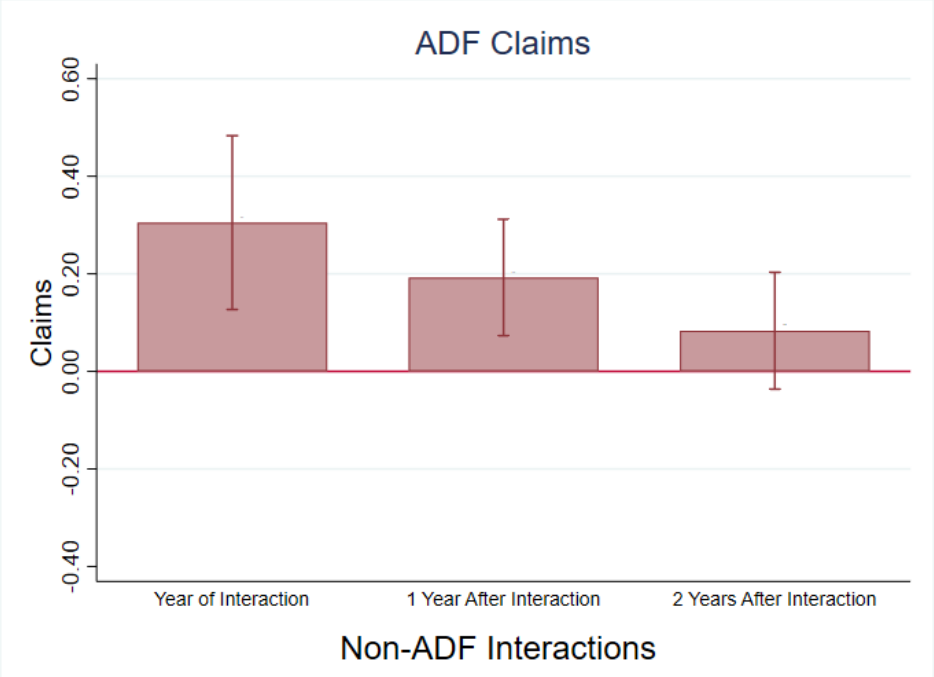

Figure B.9.: Effect of Non-ADF Interactions on ADF Claims

Figure B.10.: Effect of ADF-Only Interactions on Generic Claims

Figure B.11.: Effect of Non-ADF Interactions on Generic Claims

Table B.4.: Effect of Opioid Marketing Interactions on Patented Opioid Claims (2014-2017)

	(1)	(2)	(3)	(4)	(5)
Interactions	2.975***	2.146***	2.082***	0.710***	0.728***
	(0.140)	(0.108)	(0.112)	(0.0628)	(0.0638)
InteractionsSQ					-0.000143
					(0.000351)
Mean Dep Var = 17.66					
Percent Change	16.8%	12.2%	11.8%	4.0%	4.1%
Controls	No	Yes	Yes	Yes	Yes
Zip Code x Year FEs	No	No	Yes	Yes	Yes
Physician FEs	No	No	No	Yes	Yes
N	177,227	177,227	177,227	177,227	177,227
R^2	0.258	0.420	0.518	0.935	0.935

Robust standard errors in parentheses. Clustered at zip code level. Mean Interactions=3.19. Control are physician-level variables that include the number of: non-opioid claims, other physicians in group, Part D beneficiaries, Part D beneficiaries under the age of 65, low-income subsidy claims, female beneficiaries, female beneficiaries, black beneficiaries, beneficiaries on Medicare and Medicaid (dual). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.5.: Effect of Opioid Marketing Interactions on Generic Opioid Claims (2014-2017)

	(1)	(2)	(3)	(4)	(5)
Interactions	28.17***	12.80***	12.21***	5.260***	
	(1.600)	(0.879)	(0.899)	(0.501)	
Patented-only					5.132***
					(0.501)
Mean Dep Var = 463.92					
Percent Change	6.1%	2.8%	2.6%	1.1%	1.1%
Controls	No	Yes	Yes	Yes	Yes
Zip Code x Year FEs	No	No	Yes	Yes	Yes
Physician FEs	No	No	No	Yes	Yes
N	177,227	177,227	177,227	177,227	177,227
R^2	0.133	0.605	0.676	0.969	0.969

Robust standard errors in parentheses. Clustered at zip code level. Mean Interactions=3.19. Control are physician-level variables that include the number of: non-opioid claims, other physicians in group, Part D beneficiaries, Part D beneficiaries under the age of 65, low-income subsidy claims, female beneficiaries, female beneficiaries, black beneficiaries, beneficiaries on Medicare and Medicaid (dual), generic+patented marketing, generic-only marketing.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.6.: Effect of Opioid Marketing Interactions (2014-2017)

	Patented Claims	Generic Claims
Food & Beverage Interactions	0.627***	6.354***
	(0.0898)	(0.752)
Food & Beverage ($)	0.00957*	0.0184
	(0.00529)	(0.0341)
Other Interactions	0.230	2.545
	(0.344)	(2.060)
Other Interactions ($)	0.000117	-0.00431**
	(0.000380)	(0.00219)
Mean Dep Var	17.66	463.92
Zip Code x Year FEs	Yes	Yes
Physician FEs	Yes	Yes
N	177,227	177,227
R^2	0.935	0.969

Robust standard errors in parentheses. Clustered at zip code level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.7.: Effect of Marketing Interactions on Opioid Claims (2014-2017)

	Current Patented Claims	Current Generic Claims
Current Interactions	0.659***	3.136***
	(0.110)	(0.553)
Interactions 1 Year Ago	0.237***	2.159***
	(0.0794)	(0.537)
Interactions 2 Years Ago	0.0579	1.981***
	(0.0599)	(0.445)
Mean Dep Var	16.82	473.38
Zip Code x Year FEs	Yes	Yes
Physician FEs	Yes	Yes
N	75,048	75,048
R^2	0.972	0.991

Robust standard errors in parentheses. Clustered at zip code level. Mean Interactions=3.43.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.8.: Effect of Marketing Interactions on Opioid Claims (2014-2017)

	ADF Patented Claims	Non-ADF Patented Claims	Generic Claims
ADF-Only$_t$	0.448***	0.0444	4.003***
	(0.0911)	(0.0773)	(0.761)
ADF-Only$_{t-1}$	0.380***	-0.169*	2.275**
	(0.124)	(0.0979)	(1.126)
ADF-Only$_{t-2}$	0.350***	-0.185**	2.721***
	(0.0992)	(0.0744)	(0.995)
Non-ADF$_t$	0.305***	0.415***	1.489*
	(0.0909)	(0.0831)	(0.796)
Non-ADF$_{t-1}$	0.192***	0.143**	1.586***
	(0.0609)	(0.0640)	(0.565)
Non-ADF$_{t-2}$	0.0833	0.169***	1.707***
	(0.0611)	(0.0486)	(0.639)
ADF+NonADF$_t$	0.558***	0.862***	7.251***
	(0.176)	(0.148)	(1.479)
ADF+NonADF$_{t-1}$	0.410***	0.353***	4.383***
	(0.134)	(0.112)	(1.374)
ADF+NonADF$_{t-2}$	-0.0499	-0.122	1.093
	(0.137)	(0.0878)	(1.287)
N	75,048	75,048	75,048
R^2	0.967	0.957	0.991

Robust standard errors in parentheses. Clustered at zip code level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.9.: Effect of Marketing Interactions on Opioid Claims (2014-2016) Full Sample

	Patented Claims	Generic Claims
Interactions	0.702***	6.837***
	(0.271)	(1.949)
Mean Dep Var	3.2	112.2
Year FEs	Yes	Yes
Physician FEs	Yes	Yes
First-stage estimates:		
Zip Code Interactions$_{-i}$	0.0018***	
	(0.0001)	
Zip Code Total Payments$_{-i}$	-3.34e-09	
	(3.05e-09)	
N	1,632,008	1,632,008
First-stage F	84.0	84.0
Hansen J (*p-value*)	0.48	0.57

Robust standard errors are clustered at the zip code level and reported in parentheses. Instruments (zip code level, exclusing physician i): total number of opioid interactions, total value of marketing payments.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.10.: Effect of Marketing Interactions on Opioid Claims (2014-2017) - Excluding Doctors with Top 1% Interactions (>48 visits)

	Patented Claims	Generic Claims
Interactions	0.548***	6.553***
	(0.0484)	(0.464)
Mean Dep Var	13.76	429.18
Percent Change	4.0%	1.5%
Zip Code x Year FEs	Yes	Yes
Physician FEs	Yes	Yes
N	173,633	173,633
R^2	0.926	0.970

Robust standard errors in parentheses. Clustered at zip code level.
Mean Interactions=2.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.11.: Effect of Marketing Interactions on Opioid Claims (2014-2017) - Excluding Doctors with Top 1% Opioid Payments (>$951.36)

	Patented Claims	Generic Claims
Interactions	0.648***	7.364***
	(0.0587)	(0.478)
Mean Dep Var	14.83	442.62
Percent Change	4.4%	1.7%
Zip Code x Year FEs	Yes	Yes
Physician FEs	Yes	Yes
N	173,733	173,733
R^2	0.931	0.971

Robust standard errors in parentheses. Clustered at zip code level.
Mean Interactions=2.4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.12.: Effect of Marketing Interactions on Opioid Claims (2014-2017)

	Patented Claims	Generic Claims
Purdue Pharma	0.855***	6.557***
	(0.0865)	(0.706)
Insys	0.782***	1.966***
	(0.134)	(0.724)
Galena	2.429*	15.00*
	(1.265)	(8.373)
Vertical Pharma	0.498**	3.900***
	(0.227)	(1.317)
Mallincrodt	0.635***	-1.698
	(0.185)	(1.238)
Teva	0.247	1.159
	(0.311)	(1.622)
Depomed/Jannssen	0.772***	3.818***
	(0.123)	(1.156)
Endo Pharma	0.464***	4.635***
	(0.173)	(1.041)
Pfizer	0.404***	6.253***
	(0.131)	(0.893)
Pernix/Zogenix	0.989***	2.996
	(0.248)	(2.119)
Collegium Pharma	0.926***	5.994***
	(0.210)	(1.377)
Sentynl	0.338	17.26**
	(1.107)	(7.254)
Egalet	-0.152	3.241
	(0.196)	(2.035)
Daiichi Sankyo	1.256**	25.84***
	(0.509)	(6.375)
N	170,397	170,397
R^2	0.939	0.970

Robust standard errors in parentheses. Clustered at zip code level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C. APPENDIX: ACCOUNTABLE CARE ORGANIZATIONS AND PHYSICIAN ANTIBIOTIC PRESCRIBING BEHAVIOR

Figure C.1.: Causal Directed Acyclical Graph Diagram

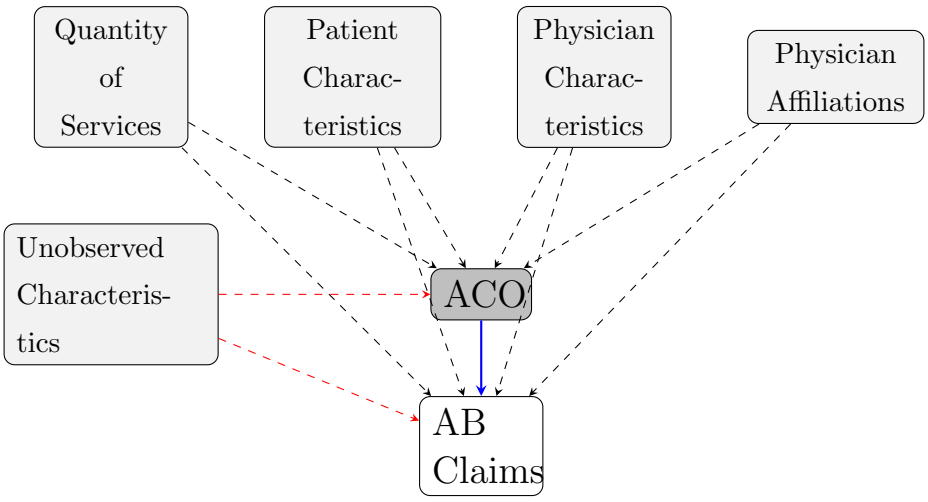

Figure C.1 shows a DAG model of antibiotic prescribing. Categories of observable variables, as well as unobserved characteristics, have a causal effect on both ACO membership and antibiotic prescribing. ACO membership itself also has a causal effect on antibiotic prescribing.

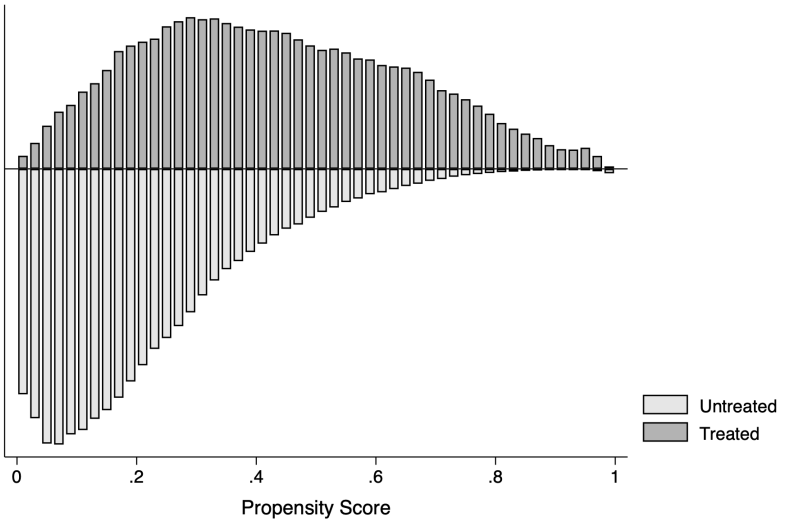

Figure C.2.: Propensity score distributions

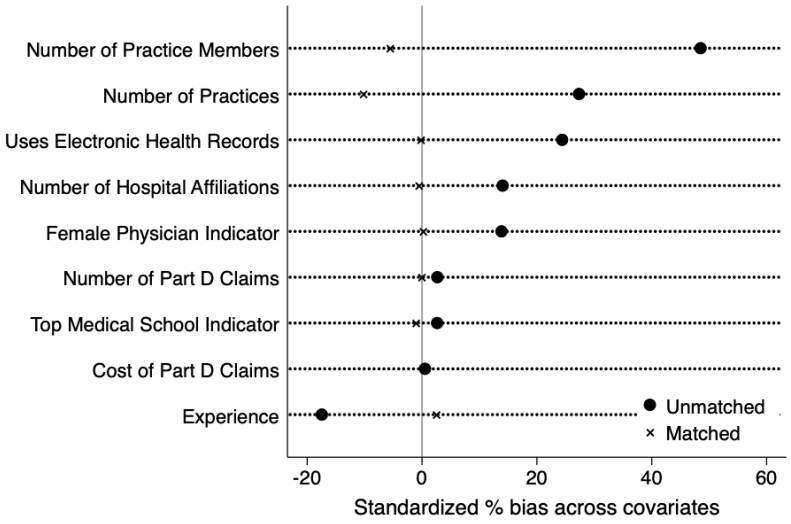

Figure C.3.: Balance pre- and post-propensity score matching: Physician Affiliations and Characteristics

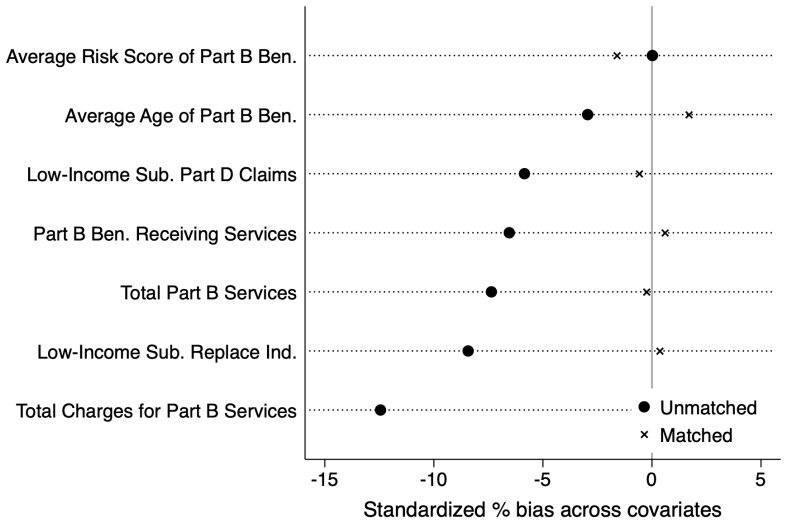

Figure C.4.: Balance pre- and post-propensity score matching: Patient Characteristics and Volume

Table C.1.: Summary Statistics by ACO Participation

	ACO=1		ACO=0		
Variable	**Mean**	**SD**	**Mean**	**SD**	**Diff.**
Outcome Variable					
Antibiotic Claims	71.88	119.11	72.70	133.52	0.82***
Physician Affiliations					
Number of Practices	1.27	0.58	1.11	0.52	-0.16***
Number of Hospital Affiliations	2.18	1.44	1.85	1.51	-0.34***
Number of Practice Members	631.85	747.04	262.86	647.86	-368.99***
Physician Characteristics					
Top Medical School Indicator	0.14	0.35	0.13	0.33	-0.02***
Uses Electronic Health Records	0.44	0.50	0.32	0.47	-0.12***
Experience	19.36	12.03	21.56	12.88	2.20***
Female Physician Indicator	0.43	0.50	0.38	0.48	-0.06***
Patient Characteristics					
Average Age of Part B Ben.	71.19	4.98	71.13	5.52	-0.06***
Average Risk Score of Part B Ben.	1.69	0.76	1.63	0.81	-0.06***
Number of Female Part B Ben.	206.19	249.63	211.39	240.17	5.21***
Low-Income Sub. Part D Claims	823.72	2,002.81	951.61	2,673.48	127.89***
Low-Income Sub. Replace Ind.	0.06	0.23	0.08	0.27	0.02***
Quantity of Services					
Number of Part D Claims	2,229.57	3,741.34	2,109.91	4,028.09	-119.67***
Cost of Part D Claims	231,228.30	441,038.90	222,856.10	460,859.20	-8,372.17***
Total Part B Services	2,568.95	12,111.98	3,550.19	18,896.36	981.24***
Total Charges for Part B Services	338,203.10	671,071.90	417,216.80	968,628.40	79,013.64***
Part B Ben. Receiving Services	368.32	457.25	371.96	428.93	3.65***
N	300,023		820,667		

Total Observations = 1,120,690
Total Physicians = 645,620

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2.: Summary Statistics for Select Specialties

	Internal Medicine	**Family & General Practitioners**	**Nurse Practitioners**
All Physicians			
% of Total Antibiotic Claims	27.2	29.1	10.9
% of Specialty in ACO	32.4	31.0	29.4
Mean Antibiotic Claims	131.51	154.28	61.70
N	167,792	152,969	143,384
Antibiotic Prescribers			
% of Total Antibiotic Claims	27.2	29.1	10.9
% of Specialty in ACO	31.9	31.1	30.1
Mean Antibiotic Claims	143.44	160.46	84.43
N	153,836	147,082	104,787

Table C.3.: Effect on Antibiotic Claims (2016-2017) - Ordinary Least Squares (OLS)

	All	All	Prescribers	Prescribers
	(1)	(2)	(3)	(4)
ACO Participation				
ACO Participation	-2.556***	1.281***	-4.788***	-0.623
	(0.222)	(0.266)	(0.292)	(0.416)
ACO x Internal Medicine		-14.53***		-12.07***
		(0.620)		(0.733)
ACO x Family & General Practice		-12.37***		-10.56***
		(0.678)		(0.761)
ACO x Nurse Practitioner		4.394***		4.678***
		(0.559)		(0.712)
Physician Affiliations				
Number of Practices	0.668***	0.732***	0.704**	0.780***
	(0.196)	(0.196)	(0.290)	(0.290)
Number of Hospital Affiliations	1.112***	1.089***	1.545***	1.530***
	(0.107)	(0.107)	(0.169)	(0.169)
Number of Practice Members	-0.000**	-0.000***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Physician Characteristics				
Top Medical School Indicator	-2.740***	-2.674***	-3.559***	-3.502***
	(0.314)	(0.314)	(0.441)	(0.441)
Uses Electronic Health Records	-7.030***	-6.764***	-9.295***	-8.981***
	(0.266)	(0.265)	(0.376)	(0.376)
Female Physician Indicator	-4.663***	-4.579***	-6.397***	-6.290***
	(0.252)	(0.251)	(0.387)	(0.386)
Patient Characteristics				
Average Age of Part B Ben.	1.345***	1.334***	1.080***	1.078***
	(0.0307)	(0.0306)	(0.0597)	(0.0596)
Average Risk Score of Part B Ben.	-4.106***	-4.118***	-4.485***	-4.481***
	(0.178)	(0.177)	(0.254)	(0.254)
Number of Female Part B Ben.	-0.0491***	-0.0484***	-0.0590***	-0.0588***
	(0.007)	(0.007)	(0.010)	(0.010)
Low-Income Sub. Part D Claims	-0.003***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Low-Income Sub. Replace Ind.	-15.770***	-15.630***	-25.520***	-25.190***
	(0.192)	(0.192)	(0.433)	(0.432)
Quantity of Services				
Number of Part D Claims	0.025***	0.025***	0.024***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Cost of Part D Claims	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Part B Services	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Charges for Part B Services	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Part B Ben. Receiving Services	0.043***	0.043***	0.068***	0.068***
	(0.004)	(0.004)	(0.006)	(0.006)
Observations	1,120,690	1,120,690	777,172	777,172
Specialty FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.629	0.630	0.620	0.620

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4.: Effect on Antibiotic Claims (2016-2017) - Two-Step Estimation Results.

	All	All	Prescribers	Prescribers
	(1)	(2)	(3)	(4)
Accountable Care Organization Participation				
ACO Participation	-18.183***	-10.386***	-23.899***	-15.707***
	(2.033)	(1.223)	(3.082)	(3.164)
ACO × Internal Medicine		-14.069***		-11.445***
		(0.478)		(0.730)
ACO × Family & General Practice		-11.908***		-9.929***
		(0.503)		(0.768)
ACO × Nurse Practitioner		4.720***		5.186***
		(0.518)		(0.719)
Physician Affiliations				
Number of Practices	1.763***	1.537***	2.117***	1.873***
	(0.244)	(0.166)	(0.369)	(0.370)
Number of Hospital Affiliations	1.256***	1.195***	1.670***	1.625***
	(0.111)	(0.066)	(0.172)	(0.171)
Number of Practice Members	0.002***	0.001***	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Physician Characteristics				
Top Medical School Indicator	-2.799***	-2.718***	-3.603***	-3.537***
	(0.314)	(0.234)	(0.441)	(0.441)
Uses Electronic Health Records	-5.732***	-5.812***	-7.510***	-7.606***
	(0.288)	(0.209)	(0.430)	(0.432)
Female Physician Indicator	-4.272***	-4.294***	-5.889***	-5.903***
	(0.251)	(0.185)	(0.387)	(0.387)
Patient Characteristics				
Average Age of Part B Ben.	1.378***	1.358***	1.101***	1.094***
	(0.030)	(0.018)	(0.059)	(0.059)
Average Risk Score of Part B Ben.	-4.164***	-4.159***	-4.629***	-4.590***
	(0.176)	(0.129)	(0.249)	(0.249)
Number of Female Part B Ben.	-0.050***	-0.049***	-0.059***	-0.059***
	(0.007)	(0.002)	(0.010)	(0.010)
Low-Income Sub. Part D Claims	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.000)	(0.001)	(0.001)
Low-Income Sub. Replace Ind.	-16.164***	-15.921***	-26.628***	-26.050***
	(0.198)	(0.307)	(0.458)	(0.457)
Quantity of Services				
Number of Part D Claims	0.025***	0.025***	0.024***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Cost of Part D Claims	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Part B Services	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Charges for Part B Services	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Part B Ben. Receiving Services	0.044***	0.043***	0.068***	0.068***
	(0.004)	(0.001)	(0.006)	(0.006)
$\rho\sigma$	9.273***	6.806***	11.338***	8.745***
	(1.184)	(0.698)	(1.800)	(1.813)
Observations	1,120,690	1,120,690	777,172	777,172
Specialty FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R-squared	0.629	0.630	0.620	0.620

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.5.: Summary Statistics

	All		Prescribers	
Variable	**Mean**	**SD**	**Mean**	**SD**
Antibiotic Claims	72.48	129.82	104.52	144.76
ACO Participation	0.27	0.44	0.28	0.45
Physician Affiliations				
Number of Practices	1.15	0.55	1.15	0.54
Number of Hospital Affiliations	1.94	1.50	2.08	1.48
Number of Practice Members	361.64	695.30	330.70	661.89
Physician Characteristics				
Top Medical School Indicator	0.13	0.34	0.13	0.33
Uses Electronic Health Records	0.35	0.48	0.36	0.48
Experience	20.97	12.70	20.90	12.57
Female Physician Indicator	0.39	0.49	0.39	0.49
Patient Characteristics				
Average Age of Part B Ben.	71.14	5.38	71.79	4.44
Average Risk Score of Part B Ben.	1.65	0.80	1.65	0.80
Number of Female Part B Ben.	210.00	242.75	215.04	218.22
Low-Income Sub. Part D Claims	917.37	2,512.18	1,139.97	2,913.90
Low-Income Sub. Replace Ind.	0.07	0.26	0.03	0.18
Other Controls				
Number of Part D Claims	2,141.94	3,953.71	2,687.16	4,521.36
Cost of Part D Claims	225,097.45	455,652.46	262,304.76	491,758.62
Total Part B Services	3,287.50	17,347.67	3,903.08	20,134.50
Total Charges for Part B Services	396,063.82	899,358.90	405,719.78	910,958.75
Part B Ben. Receiving Services	370.99	436.69	379.65	393.41
N	1,120,690		777,172	

Table C.6.: First-Stage Probit Regression Results

VARIABLES	Full	Prescribers
	(1)	(2)
Physician Affiliations		
Number of Practices	0.260***	0.265***
	(0.003)	(0.004)
Number of Hospital Affiliations	0.030***	0.021***
	(0.001)	(0.002)
Number of Practice Members	0.000***	0.000***
	(0.000)	(0.000)
Physician Characteristics		
Top Medical School Indicator	-0.009*	-0.000
	(0.005)	(0.006)
Uses Electronic Health Records	0.329***	0.352***
	(0.004)	(0.005)
Female Physician Indicator	0.058***	0.059***
	(0.004)	(0.005)
Experience	-0.007***	-0.008***
	(0.000)	(0.000)
Patient Characteristics		
Average Age of Part B Ben.	0.008***	0.005***
	(0.000)	(0.001)
Average Risk Score of Part B Ben.	-0.018***	-0.034***
	(0.003)	(0.003)
Number of Female Part B Ben.	-0.000***	0.000
	(0.000)	(0.000)
Low-Income Sub. Part D Claims	-0.000***	-0.000***
	(0.000)	(0.000)
Low-Income Sub. Replace Ind.	-0.106***	-0.231***
	(0.007)	(0.011)
Quantity of Services		
Number of Part D Claims	0.000***	0.000***
	(0.000)	(0.000)
Cost of Part D Claims	-0.000*	-0.000
	(0.000)	(0.000)
Total Part B Services	-0.000**	-0.000
	(0.000)	(0.000)
Total Charges for Part B Services	-0.000***	-0.000***
	(0.000)	(0.000)
Part B Ben. Receiving Services	0.000***	-0.000
	(0.000)	(0.000)
Observations	1,120,690	777,172
Specialty FE	YES	YES
Year FE	YES	YES
HRR FE	YES	YES
RUCA FE	YES	YES

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.7.: Censoring: Imputation and Maximum Likelihood Results Comparison

	All Impute (1)	All Impute (2)	All ML (3)	All ML (4)
ACO Participation	-2.556***	1.281***	-2.563***	1.277***
	(0.222)	(0.266)	(0.221)	(0.264)
ACO x Internal Medicine		-14.53***		-14.527***
		(0.620)		(0.617)
ACO x Family & General Practice		-12.37***		-12.339***
		(0.678)		(0.676)
ACO x Nurse Practitioner		4.394***		4.416***
		(0.559)		(0.554)
Observations	1,120,690	1,120,690	1,129,773	1,129,773
Specialty FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.629	0.630	0.620	0.620

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.8.: Effect on Antibiotic Claims (2016) - OLS Estimation Results

	All	All	Prescribers	Prescribers
	(1)	(2)	(3)	(4)
ACO Participation				
ACO Participation	-2.957***	0.512	-5.460***	-2.049***
	(0.274)	(0.334)	(0.359)	(0.534)
ACO x Internal Medicine		-12.28***		-9.449***
		(0.709)		(0.855)
ACO x Family & General Practice		-11.37***		-9.246***
		(0.787)		(0.900)
ACO x Nurse Practitioner		5.534***		6.154***
		(0.678)		(0.876)
Physician Affiliations				
Number of Practices	0.338	0.398*	0.624*	0.696**
	(0.220)	(0.220)	(0.342)	(0.342)
Number of Hospital Affiliations	1.425***	1.398***	1.758***	1.740***
	(0.119)	(0.119)	(0.190)	(0.190)
Number of Practice Members	-0.000450**	-0.000606***	-0.00192***	-0.00201***
	(0.000182)	(0.000182)	(0.000281)	(0.000281)
Physician Characteristics				
Top Medical School Indicator	-2.810***	-2.755***	-3.636***	-3.595***
	(0.324)	(0.324)	(0.457)	(0.456)
Uses Electronic Health Records	-5.958***	-5.774***	-7.878***	-7.667***
	(0.296)	(0.295)	(0.416)	(0.417)
Female Physician Indicator	-4.504***	-4.423***	-5.834***	-5.736***
	(0.273)	(0.272)	(0.408)	(0.408)
Patient Characteristics				
Average Age of Part B Ben.	1.366***	1.353***	1.151***	1.148***
	(0.0330)	(0.0329)	(0.0672)	(0.0672)
Average Risk Score of Part B Ben.	-2.666***	-2.661***	-3.060***	-3.041***
	(0.201)	(0.201)	(0.283)	(0.282)
Number of Female Part B Ben.	-0.0542***	-0.0536***	-0.0696***	-0.0694***
	(0.00722)	(0.00721)	(0.0119)	(0.0119)
Low-Income Sub. Part D Claims	-0.00145***	-0.00153***	-0.00113**	-0.00118**
	(0.000453)	(0.000453)	(0.000491)	(0.000491)
Low-Income Sub. Replace Ind.	-13.78***	-13.62***	-24.76***	-24.38***
	(0.230)	(0.230)	(0.531)	(0.530)
Quantity of Services				
Number of Part D Claims	0.0240***	0.0241***	0.0238***	0.0238***
	(0.000204)	(0.000204)	(0.000232)	(0.000232)
Cost of Part D Claims	-0.0000125***	-0.0000125***	-0.00000624***	-0.00000628***
	(0.000000781)	(0.000000780)	(0.000000947)	(0.000000947)
Total Part B Services	0.000174***	0.000174***	0.0000811***	0.0000818***
	(0.0000167)	(0.0000167)	(0.0000223)	(0.0000223)
Total Charges for Part B Services	0.000000123	0.000000152	0.000000738	0.000000769
	(0.000000290)	(0.000000290)	(0.000000546)	(0.000000546)
Part B Ben. Receiving Services	0.0449***	0.0446***	0.0732***	0.0731***
	(0.00417)	(0.00417)	(0.00585)	(0.00585)
Observations	526,001	526,001	365,431	365,431
Specialty FE	YES	YES	YES	YES
Year FE	NO	NO	NO	NO
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.646	0.647	0.637	0.637

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.9.: Effect on Antibiotic Claims (2017) - OLS Estimation Results

	All	All	Prescribers	Prescribers
	(1)	(2)	(3)	(4)
ACO Participation				
ACO Participation	-2.323***	1.816***	-4.408***	0.312
	(0.262)	(0.305)	(0.346)	(0.467)
ACO x Internal Medicine		-16.86***		-14.60***
		(0.730)		(0.854)
ACO x Family & General Practice		-13.30***		-11.67***
		(0.780)		(0.869)
ACO x Nurse Practicioner		3.378***		3.428***
		(0.641)		(0.819)
Physician Affiliations				
Number of Practices	0.971***	1.040***	0.798**	0.882***
	(0.215)	(0.215)	(0.322)	(0.323)
Number of Hospital Affiliations	0.826***	0.807***	1.338***	1.325***
	(0.126)	(0.126)	(0.219)	(0.219)
Number of Practice Members	-0.000222	-0.000349**	-0.00121***	-0.00129***
	(0.000169)	(0.000170)	(0.000282)	(0.000282)
Physician Characteristics				
Top Medical School Indicator	-2.665***	-2.587***	-3.464***	-3.391***
	(0.327)	(0.327)	(0.459)	(0.459)
Uses Electronic Health Records	-8.095***	-7.727***	-10.70***	-10.25***
	(0.320)	(0.320)	(0.464)	(0.464)
Female Physician Indicator	-4.785***	-4.696***	-6.850***	-6.735***
	(0.261)	(0.260)	(0.409)	(0.408)
Patient Characteristics				
Average Age of Part B Ben.	1.324***	1.315***	1.013***	1.015***
	(0.0342)	(0.0340)	(0.0773)	(0.0771)
Average Risk Score of Part B Ben.	-5.261***	-5.290***	-5.650***	-5.661***
	(0.179)	(0.179)	(0.260)	(0.259)
Number of Female Part B Ben.	-0.0444***	-0.0435***	-0.0495***	-0.0492***
	(0.00700)	(0.00700)	(0.0110)	(0.0110)
Low-Income Sub. Part D Claims	-0.00378***	-0.00389***	-0.00370***	-0.00377***
	(0.000571)	(0.000567)	(0.000637)	(0.000634)
Low-Income Sub. Replace Ind.	-17.29***	-17.16***	-25.97***	-25.68***
	(0.235)	(0.234)	(0.554)	(0.553)
Quantity of Services				
Number of Part D Claims	0.0249***	0.0249***	0.0249***	0.0249***
	(0.000207)	(0.000206)	(0.000248)	(0.000248)
Cost of Part D Claims	-0.0000128***	-0.0000128***	-0.00000658***	-0.00000666***
	(0.000000853)	(0.000000849)	(0.00000108)	(0.00000107)
Total Part B Services	0.000181***	0.000182***	0.000112***	0.000113***
	(0.0000165)	(0.0000165)	(0.0000231)	(0.0000230)
Total Charges for Part B Services	-9.42e-08	-5.50e-08	0.000000376	0.000000422
	(0.000000306)	(0.000000305)	(0.000000722)	(0.000000720)
Part B Ben. Receiving Services	0.0421***	0.0417***	0.0637***	0.0636***
	(0.00407)	(0.00407)	(0.00620)	(0.00620)
Observations	594,689	594,689	411,741	411,741
Specialty FE	YES	YES	YES	YES
Year FE	NO	NO	NO	NO
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.614	0.614	0.604	0.605

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.10.: Average Treatment Effect on the Treated (ATT) Results

	Full	Prescribers
	(1)	(2)
ATT	-3.248***	-4.237***
	(0.467)	(0.595)

Propensity scores computed using probit regression.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

VITA

Svetlana N. Beilfuss

Contact Information

Department of Economics
Krannert Building,
Purdue University
West Lafayette, Indiana 47907-2056

Phone: (734) 904-4491
E-mail: sbeilfus@purdue.edu
Web: svetlanabeilfuss.com

Research Interests

Health Economics; Labor Economics; Public Economics; Public Policy

Education

Purdue University — **West Lafayette, IN**

PhD, Economics — August 2020

Committee: Victoria Prowse (co-chair), Jillian Carr (co-chair), Timothy J. Moore, Kevin Mumford, Brigitte Waldorf

Eastern Michigan University — **Ypsilanti, MI**

MA, Applied Economics; Health Economics Certificate — August 2014

University of Michigan — **Ann Arbor, MI**

BA, Russian and East European Studies; Economics — May 2007

Publications

"New Evidence on Factors Affecting the Level and Growth of US Health Care Spending"
Applied Economics Letters, 2016, 23(1), pp 15-18 (with James Thornton)

"Pathways and Hidden Benefits of Healthcare Spending Growth in the US"
Atlantic Economic Journal, 2016, 44(3), pp 363-375 (with James Thornton)

Working Papers

"Pharmaceutical Opioid Marketing and Physician Prescribing Behavior"

"Inertia and Switching in Health Insurance Plans"

"Accountable Care Organizations and Physician Antibiotic Prescribing Behavior"
(with Sebastian Linde and Brandon Norton)

Work in Progress

"Hospital Mergers and Integration with Physician Practices"
(with Brandon Norton)

Awards

Purdue University

Finalist in the Three Minute Thesis (3MT) research presentation competition, 2019
Distinguished Teaching Award for Microeconomics, 2017
Distinguished Recitation Teaching Award for Principles of Economics, 2016

Eastern Michigan University

Hanna Award for Outstanding Paper Using Quantitative Methods, 2014
Lecturer of the Year Award, 2014
Academic Achievement Award - Graduate Student with Highest GPA (4.0), 2014

Academic Achievement Award - Graduate Student with Highest GPA (4.0), 2013

University Fellowship, 2013

Omicron Delta Epsilon International Honor Society in Economics, 2013

Teaching Experience

Instructor

Principles of Microeconomics (Purdue), 2017 - evaluations: 4.7/5.0

Principles of Economics Recitation (Purdue), 2016 - evaluations: 4.8/5.0

Principles of Microeconomics (Eastern Michigan University), 2014

Principles of Macroeconomics (Eastern Michigan University), 2014

Instructor Online

Economics and Society (Mid Michigan College), 2013, 2014, 2015, 2016, 2017, 2018, 2019

Principles of Microeconomics (Mid Michigan College), 2013, 2015, 2016, 2017, 2018, 2019

Principles of Macroeconomics (Mid Michigan College), 2018, 2019

Teaching Assistant

Health Economics (Purdue), 2019

Econometrics (Purdue), 2018, 2019

Behavioral Economics (Purdue), 2017

Public Finance and Taxation (Purdue), 2015, 2019

Government Finance (Eastern Michigan University), 2014

Econometrics I (Eastern Michigan University), 2013

Advanced Microeconomics (Eastern Michigan University), 2013

Research Experience

Research Assistant

Research Assistant to Victoria Prowse, 2016, 2017, 2018

Research Assistant to Jillian Carr, 2016, 2018

Conference Presentations

Southern Economic Association Conference, 2019

American Society of Health Economists (ASHEcon), 2019

Midwest Economics Association Conference (SOLE Session), 2019

Southern Economic Association Conference, 2018

Midwest Economics Association Conference (SOLE Session), 2018

Southern Economic Association Conference, 2014

Midwest Economics Association Conference, 2014

Michigan Academy of Science Arts & Letters Conference, 2014

Computer Skills

LaTeX, Stata, SAS, MATLAB, EViews, Moodle

Citizenship

United States