Welfare Effects of Physician-industry Interactions: Evidence From Patent Expiration

(PRELIMINARY — do not cite without permission)

Aaron Chatterji*, Matthew Grennan†, Kyle Myers‡, Ashley Swanson†

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Abstract

Many transactions occur via expert advisors, especially in the healthcare sector, and as such, firms frequently implement strategies to influence these advisors. The efficiency of these interactions is an empirical question. Using data on physician-industry interactions and prescribing behavior during the entry of a major generic statin drug, we examine the causal effect and welfare implications of the most common type of interaction: meals. Guided by a theoretical model of endogenous meals, we develop an instrumental variables identification strategy and document evidence that these meals directly influence prescribing decisions. We find that firms target meals to prescribers with an otherwise low propensity to use the target drug. Given this evidence, we estimate a structural model of drug choice and pricing that allows us to predict counterfactual outcomes in a world where these meals are banned. Results from these counterfactuals are in line with theoretical predictions that these interactions can offset efficiency losses due to pricing with market power. However, in our model estimates for this particular market and time period, the high relative prices of branded drugs outweigh these allocative gains.

*Duke University, The Fuqua School & NBER

†University of Pennsylvania, The Wharton School & NBER

‡NBER

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1 Introduction

Interactions between firms and consumers often occur via expert advisers. In health care and financial services, for example, consumers often select a product in conjunction with an intermediary, typically a physician or a certified financial adviser. These experts can theoretically provide valuable information about complex products, helping to increase market efficiency. However, because these experts sometimes receive remuneration from firms selling in the market, their advice may be biased. Whether and how this bias impacts efficiency are contentious and important policy questions, animating debates over recent initiatives in the United States to address conflicts of interest (including the Physician Payment Sunshine Act (2010) and Department of Labor's Fiduciary Rule (2016)), and spurring a great deal of commentary (e.g., Drazen 2015; Rosenbaum 2015a,b,c; and Steinbrook et al. 2015).

Economists have long been interested in studying these types of conflicts and tradeoffs across various settings where information is imperfect and contracts are costly to enforce.[1] The pharmaceutical industry offers an ideal setting to study the costs and benefits of expert-industry interactions. In the US pharmaceutical industry, many physicians receive payments and other in-kind compensation, such as meals, from companies that produce products they can prescribe, inject, or recommend.[2] The ubiquity of these practices led to the entire May 2017 issue of the *Journal of the American Medical Association* being devoted to the topic of conflict of interest in medicine. Moreover, granular data on drug utilization linked to physician identifiers is readily available. Finally, the drug approval process implies that welfare analysis can incorporate both revealed preference measures and cost-effectiveness data from clinical trials. This is a helpful validation tool in settings where revealed preference demand estimates may capture behavioral frictions or agency problems.

Most of the empirical studies on this topic to date document positive correlations between firms' payments to physicians and prescribing of those firms' products.[3] It is unclear whether these correlations represent causal evidence of inducement, as both physicians and

[1] This literature is perhaps best developed for financial services industries. E.g., Michaely and Womack (1999) document that brokerage analysts' comments and recommendations can be biased by their firms' affiliations, and that the market does not recognize the full extent of this bias.

[2] Remuneration may also take the form of consultant fees, educational grants, royalties, funding for clinical trials, or travel grants. Millenson (2003) prevents an overview of these practices for drugs and medical devices such as hip and knee implants and cardiac stents.

[3] Kremer et al. (2008) provides a review of early research on this topic, noting that physician responsiveness appears to vary across drugs and that studies accounting for the endogeneity of interactions find lower responsiveness. In one recent example, Yeh et al. (2016) found an association between industry payments to physicians and the prescribing of brand-name statins; they also found that this association was no longer significant when the analysis was limited to physicians who received $2,000 or less in total payments. In contrast, DeJong et al. (2016) found that physicians who received a single meal promoting the drug of interest had higher rates of prescribing promoted drugs in several popular classes.

the patients they treat may have unobservably different preferences over substitute products. Even if payments bias physician decisions toward the sponsoring firm, the implications for efficiency are unclear. If patients consume too little of a high-quality product due to manufacturer market power, countervailing payments from competitors, or other behavioral or market frictions, then this bias may increase utilization toward the optimum, though perhaps at great cost to patients and/or payers.

Our study fits into a rich literature on the complex welfare effects of the marketing behavior of pharmaceutical manufacturers.[4] In our study, we focus on payments from manufacturers to physicians, which is just one component of firms' promotional strategies. These generally include direct-to-consumer advertising, sales visits to physicians (also called "detailing"), advertisements in venues targeted to physicians, and payments.[5] The study that is closest to ours is Carey et al. (2017): in this work, the authors analyze unprecedentedly rich prescribing data linked to physicians' payments from pharmaceutical manufacturers. They show that payments from a drug firm raise expenditures on the firm's products, even within physician; the results also hold when focusing on patients who changed prescribers. They further analyze the impact of payments on four major patent expirations – Lipitor, Singulair, Seroquel, and Lexapro – finding that prescribers who had received payments transitioned their patients to the generic equivalents just as quickly as prescribers with no payments.[6]

We contribute to these literatures in several ways. First, as in Carey et al. (2017), we examine the effects of payments to physicians, which are expected to have different implications for efficiency than advertising to consumers. Second, we develop an identification strategy that accounts for potential endogeneity introduced by the strategic targeting of physicians

[4]As noted in Scott Morton and Kyle (2012), promotion of pharmaceuticals embodies both potential inducements to use firms' products and some scientific information. Such promotion will likely expand the market overall and include some business-stealing; in some cases, firms would like to commit not to advertise for this reason. In 2009, the industry trade association PhRMA introduced a voluntary Code on Interactions with Healthcare Professionals limiting informational presentations to the workplace and entertainment to "modest meals," and prohibiting trips to resorts, sponsored recreation, and gifts to the physicians.

[5]Several studies present nuanced, causal evidence of the effects of direct-to-consumer advertising (DTCA). Shapiro (2016) uses discontinuities in advertising along the borders of television markets to estimate significant positive effects of television advertising on use of prescription antidepressants. Sinkinson and Starc (2015) exploit shocks to local advertising markets generated by the political advertising cycle to show significant positive effects of statin advertising on demand, as well as positive spillovers from drug advertisements to non-advertised competitors in the same class. Alpert et al. (2015) examine a large shock to advertising driven by the introduction of Medicare Part D in 2006 and find substantial differential increases in drug utilization that mirror the increases in DTCA after Part D. While the literature on DTCA is somewhat more developed, there is also compelling recent evidence on the effects of detailing: Larkin et al. (2017) examine the effects of changes in US academic medical centers' policies restricting detailing between 2006 and 2012. They find that restricted detailing was associated with modest but significant reductions in prescribing of detailed drugs across 6 of 8 major drug classes, including statins and antidepressants.

[6]At least two other published studies we are aware of incorporate physician-level fixed effects: Mizik et al. (2004) and Datta et al. (2015).

by pharmaceutical firms. Third, as in many of the advertising papers, we estimate structural models of demand and supply and shed light on the welfare effects of demand inducement in the presence of market power. We then use these to inform an examination of the potential welfare implications of a ban on these types of physician-industry interactions.[7] Bans are a policy-relevant counterfactual to examine: financial advisors in the United Kingdom are banned from accepting commissions in return for recommending specific investment products[8], and Minnesota's Fair Drug Marketing Law prohibits gifts over $50.

To motivate our analyses, we develop a model of physician prescribing and firm payment and pricing behavior in the market for a popular class of cholesterol-reducing drugs known as statins. During our period of study, there were two branded statins (Pfizer's Lipitor and AstraZeneca's Crestor) and several generic substitute statins. In the model, prescribing decisions are a function of preferences over branded and generic substitutes, prices, and meals. Meals are a popular variety of in-kind payment from pharmaceutical firms to physicians, and the one we focus on in our study. We model drug prices and meals before and after Lipitor's patent expires. The first order conditions in the firm's problem demonstrate how prices and meals respond optimally to patent expiration, and how meals are impacted by variation in the costs of interacting with physicians. The latter first-order condition motivates our causal identification strategy, which we use in several analyses of the effects of meals on prescribing. We estimate our models using a comprehensive dataset on firm-physician-year-level meals from early firm disclosures of payments, linked to physician-drug-year-level prices and quantities observed in a large market – the Medicare Part D prescription drug insurance program for the elderly in the US.

Our identification strategy relies on the fact that, due to economies of scale in setting marketing strategy to a particular physician market, a set of market and hospital-level variables are highly predictive of meals but plausibly unrelated to physicians' latent preferences over substitute products or responsiveness to payments. We use a high-dimensional set of such variables, along with a rich set of physician-level controls we expect to be correlated with preferences, and utilize LASSO regressions to select both controls and excluded instru-

[7] One might speculate that the disclosure policy embodied in the Physician Payment Sunshine Act (2010) would be analogous to a ban in its effects on conflicts of interest. Inderst and Ottaviani (2012) present a compelling model of kickbacks and competition in a setting such as ours, demonstrating that disclosure reduces the equilibrium level of commissions and may harm welfare. However, as they note, disclosure may have limited real-world effects. Hockenberry et al. (2011) analyze data made public following a 2007 settlement between leading manufacturers of joint implants and the Department of Justice; interestingly, the authors find that payments to surgeons *increased* following said settlement. Pham-Kanter et al. (2012) study the experience of two states, Maine and West Virginia, that previously implemented drug payment disclosure laws. They show that these laws had a negligible to small effect on physicians switching from branded therapies to generics and no effect on reducing prescription costs.

[8] See Policy Statement 10/6 by the UK Financial Services Authority, released on March 26, 2010.

ments. The richness of our data allows us to examine extensive margin, intensive margin, and nonlinear effects of payments on utilization – most interactions are small $20-50 meals. We also examine heterogeneity in treatment effects with respect to physicians' age and training.

Our 2SLS regression results indicate that meal receipt caused a large causal increase in both Lipitor and Crestor claims. The effects are substantially larger than simple OLS analyses would indicate, implying that although branded firms provide meals to a large number of physicians that are not heavy branded statin prescribers, the relative effect of meals among those physicians is large. The results are largest for Lipitor, consistent with Pfizer targeting high-value markets late in its life-cycle. The results are robust to omitting hospital-level instruments and, as expected, are concentrated in states without bans on high-value meals or pre-Open Payments transparency requirements. We also show that the extensive margin results are large relative to intensive margin results and that there are accordingly low marginal returns to higher-value meals, conditional on providing any meal.

We then use our structural model to provide further evidence on the welfare effects of kickbacks in markets with advisors. Our work is similar in spirit to Inderst and Ottaviani (2012), in which hidden kickbacks allow firms to expand market share without having to lower their prices at the same time. In the market for branded drugs, most consumption is insured and prices are perhaps even higher than monopoly power alone would confer, implying that kickbacks or payments may increase costs while simultaneously bringing utilization closer to efficient levels.[9]

In order to examine the interactions between market power and payments to physicians, we estimate a nested logit model of statin choice before and after a major patent expiration. In our setting, Lipitor's patent expiration results in generic entry, price changes, and changes in meals for both Lipitor and Crestor. Our structural estimates indicate that a meal has an equivalent impact to a $78 change in out of pocket price. This magnitude is partially driven by the lack of price sensitivity we observe. The primary result of the model is that while payments do increase prescribing, on average they do so in a way that offsets the underprovision of statins due to market power by about half.

Our results also highlight several of the issues motivated by Inderst and Ottaviani (2012). The extent to which payments distort the efficient allocation depends upon their scale relative to that of the distortion due to market power maintaining high prices, and to the prices, payments, and quality of drugs that are close substitutes. In the market studied here,

[9]Indeed, Huckfeldt and Knittel (2011) show that when a drug's patent expires, the total number of units of that molecule consumed, both brand and generic, falls noticeably around patent expiration, which is not what an ordinary model of demand would predict. As discussed in Section 4.4, we find that consumption increases for atorvastatin (Lipitor plus its generic alternative) after Lipitor's patent expires, but whether it increases to efficient levels is an empirical question.

payments move the market closer to the efficient allocation. However, banning payments results in an increase of $10.9M (0.8 percent) in consumer surplus. These consumer surplus losses outweigh producer gains, resulting in payments being inefficient in terms of total surplus, in spite of moving closer to the aggregate efficient allocation on the extensive margin. Banning payments results in an increase of $1.7M (0.1 percent) in total surplus in the retail market for statins. The largest effect of meal payments is to increase insurer transfers to upstream manufacturers and distributors by $21.7M (9.9 percent) in 2011 and $31.4M (20.5 percent) in 2012 relative to our counterfactual where payments are banned.

2 Setting, Data, and Empirical Strategy

Statin medications reduce blood levels of low-density lipoprotein cholesterol (LDL, or "bad" cholesterol), and in turn reduce the risk of coronary heart disease and heart attacks. In order to investigate the welfare effects of payments from statin firms to physicians, we focus on cardiologists treating enrollees in the Medicare Part D program in 2011 and 2012. This sample and time horizon are useful for several reasons. (1) We have physician-firm interaction data for the two major on-brand statin producers during this time: Pfizer (which produces Lipitor) and AstraZeneca (which produces Crestor) accounted for 49 percent and 33 percent of statin revenue in Medicare Part D in our sample in 2011, respectively. This is before the Open Payments website created under the Physician Payment Sunshine Act was published, implying that we can analyze the effects of payments prior to the shock of broad disclosure. (2) These statins were each the chief source of revenue from cardiologists' prescribing for these two firms, with Lipitor accounting for 84% of Pfizer's cardiologist-driven revenues and Crestor similarly accounting for 80% of AstraZeneca's cardiologist-driven revenues. Thus, if a Pfizer or AstraZeneca representative were taking a cardiologist out to lunch in this time period, it is very likely that statins were the focus of any drug-related discussions. (3) Lipitor's patent expiration offers a large and visible shock to statin prices, enabling us to identify demand curves.[10]

Statins are generally considered to be effective drugs with few side effects. In 2013, the American College of Cardiology (ACC) and the American Heart Association (AHA) released guidelines recommending statin therapy for adults with elevated risk of atherosclerotic cardiovascular disease. Adoption of statins under these guidelines would have increased statin use by 24 percent.[11] Statins are close substitutes for most patients, but atorvastatin (Lipi-

[10] Carrera et al. (2018) find that cross-sectional variation in patients' copays has a modest impact on statin prescribing ($\varepsilon = -0.31$), while large changes in average copays due to patent expiration imply much larger responses ($\varepsilon = -0.76$).

[11] http://www.acc.org/latest-in-cardiology/articles/2017/04/18/15/45/study-looks-at-uspstf-vs-acc-aha-

tor) and rosuvastatin (Crestor) are available as high-intensity statins appropriate for some patients with elevated risk – a moderate-intensity statin is expected to reduce LDL by 30 to 50 percent, while a high-intensity statin would reduce LDL by 50 percent or more (ConsumerReports (2014)). We incorporate this differentiating factor into our demand model below.

The generic version of Lipitor (atorvastatin) became available at the very end of 2011. The entry of this generic drug created the customary shocks to absolute and relative prices that follow the loss of exclusivity, and at a very large scale: the total Part D expenditures associated with Lipitor dropped by more than 75%, from $2.5 billion (13 million claims) in 2011 to $591 million (2.8 million claims) in 2012. Section 2.2 provides a more detailed view of the focal cardiologists and the statin market at this time.

We examine the statin market at the end of 2011, 15 years after Lipitor was introduced and 8 years after Crestor was introduced. Moreover, statins as a class have been available since Mevacor was introduced in 1987 by Merck. By 2011, there was likely very little information regarding the atorvastatin and rosuvastatin molecules that was not available to cardiologists. The classic justification for physician-industry interactions is that they allow physicians to learn about a drug's features (e.g. indications, side-effects, dosage guidelines). In the below, when we document evidence of a causal effect of interactions on prescribing, it is unlikely to be due to firms providing new information about the promoted drugs, though interactions may act as persuasive nudges or reminders.

2.1 Sample and Data Sources

Our analyses of prescribing focus on physicians treating enrollees in the Medicare Part D program. 37 million people, or 70 percent of eligible Medicare beneficiaries enrolled in Part D plan in 2014 (Hoadley et al. (2014)). Medicare-eligible individuals can acquire prescription drug coverage through standalone Part D plans or can obtain drug coverage bundled with medical and hospital coverage in the form of "Medicare Advantage" plans. Utilization of drugs in the Part D program is a function of physicians prescribing decisions, which may be impacted by training and knowledge, interaction with pharmaceutical firms, and preferences over cost control; enrollees' decisions to fill and consume drugs as a function of effectiveness, side effects, and out-of-pocket costs; and Part D insurers' coverage policies.

Part D plans are offered by private insurers, but the federal Centers for Medicare and Medicaid Services (CMS) mandates coverage generosity of plans in terms of actuarial value, types of drugs covered, and pharmacy network breadth. Enrollees are entitled to basic

guidelines-for-statin-therapy

coverage of prescription drugs by a plan with equal or greater actuarial value to the standard Part D plan.[12]

The majority of Part D enrollees are not enrolled in standard plans, but rather in actuarially equivalent or "enhanced" plans with non-standard deductibles and tiered copays where enrollees out-of-pocket costs vary across drugs and pharmacies. Branded drugs with close generic substitutes (e.g., Lipitor and Crestor vs. simvastatin and pravastatin prior to Lipitor's patent expiration) generally have higher copays than generics, while branded drugs with generic equivalents (e.g., Lipitor vs. atorvastatin after Lipitor's patent expiration) have even higher copays or may not be covered by plans at all. Thus, the structure of Medicare Part D implies that enrollees should be sensitive to price variation across branded and generic drugs.[13] This sensitivity may be muted by various frictions, including enrollees' limited understanding of coverage and physicians' imperfect agency in prescribing.[14] Also, approximately 30 percent of Part D enrollees qualify for low-income subsidies (LIS), which entitles them to substantial reductions in premiums and out-of-pocket costs on covered drugs.[15] LIS enrollees can enroll premium-free in "benchmark plans" or enroll in a non-benchmark plan and pay the difference between the chosen plan's premium and the benchmark premium out-of-pocket. Maximum copays for LIS enrollees are low or zero.

Part D issuers receive premiums from enrollees and receive a variety of subsidy payments from CMS: risk-adjusted direct subsidies for each enrollee, additional subsidies to cover LIS premiums and cost-sharing, and reinsurance for particularly high-cost enrollees. They also receive or pay "risk corridor" transfers such that the issuers' profits/losses are within certain bounds.[16] Although issuers' behavior and profits are heavily regulated by CMS, they have both motive and opportunity to constrain costs through formulary design (drugs' coverage and placement on tiers), negotiations with drug manufacturers, and negotiations with pharmacies. Duggan and Morton (2010) show that initial introduction of Part D in 2006 lowered the price of drugs by increasing insurer market power relative to drug manufacturers. This is not to say that Part D insurers act as perfect agents of enrollees, but rather that

[12] In 2011, the standard plan covered: none of the first $310 in drug costs each year (the deductible); 75 percent of costs for the next $2,530 of drug spending (up to $2,840 total; the "initial coverage region"); 50 percent of branded costs for the next $3,607 of drug spending (up to $6,447 total; the "donut hole"); and 95 percent of costs above $6,447 in total drug spending (the "catastrophic region").

[13] See Chandra et al. (2010) and Goldman et al. (2007) for helpful reviews of the literature.

[14] For example, Abaluck et al. (2017) note that enrollees are more responsive to current prices than marginal prices (i.e., they are myopic), and that they respond disproportionately to salient coverage changes such as copay changes for entire drug classes.

[15] Partial subsidies are available at 150 percent of the federal poverty level (FPL); full subsidies are available at 100 percent of FPL.

[16] Insurers bear all upside/downside risk within a 5 percent band of zero profit; outside this risk corridor, the plan absorbs 20-25 percent of profits and losses.

they are well-incentivized to reduce costs; as demonstrated by Ho et al. (2017), drug prices in Part D plans increased only about 2 percent between 2007 and 2010, but plan premiums grew by 62.8 percent.

2.1.1 Data on Medicare Part D, prescribing, and provider characteristics

We obtain data on physician demographics, specialties, and affiliations from CMS' Physician Compare database, which contains all physicians treating Medicare patients.[17] Given the size of Medicare Part D, this population of physicians is worthy of study in its own right, even if they are not completely representative of all physicians.[18] Each physician's practice location is matched to his or her relevant Hospital Service Area (HSA) and Hospital Referral Region (HRR) according to the Dartmouth Atlas.[19]

Prescribing behavior is based on the publicly available CMS Part D claims data for 2011 and 2012.[20] These claims data describe total prescription claims and spending for each prescriber-drug-year. The prescriber information includes the National Provider Identifier (NPI), which allows us to link claims data to the Physician Compare database as well as the industry interaction data. Drugs are defined by brand and molecule name (if the drug is "generic," these two are equivalent). Loosely speaking, claims approximate prescriptions. Claims may vary in terms of unobserved drug dosages and formulation, so that we cannot express demand in terms of total days supply (see, e.g., Abaluck et al. (2017)) or total active ingredient. We are unaware of any evidence that industry payments target particular dosages or presentations, so we follow prior studies that analyze claims (Einav et al. 2015).

Our price variables are the plan-enrollment-weighted average point-of-sale price and copay (patient cost-sharing) per one-month supply for each Part D pricing region (PDP region)-drug-year from the Medicare Part D Public Use Files. One month is the modal amount supplied per prescription claim.

Using the name of the drug, we also match branded drugs in the prescribing data to their respective manufacturers using the FDA's Orange Book and match all drugs to their WHO Anatomical Therapeutic Classification (ATC) codes. The ATC codes provide a well-

[17] Available at https://data.medicare.gov/data/physician-compare.

[18] As with the numerous other studies that rely on Medicare Part D data, our study may not correctly estimate the relationship between payments and prescriptions for all physicians and all patients (i.e., including those outside the Medicare population). In terms of generalizability, we might expect physicians treating the elderly to receive higher *levels* of payments from industry given that this population accounts for a majority of prescription drug spending. However, we contend that there are no strong reasons to believe that physicians would *respond* differently to industry payments across payers; e.g., we have no reason to believe that doctors who receive large payments from industry primarily respond by increasing their prescribing of branded drugs to the non-Medicare population.

[19] See www.dartmouthatlas.org.

[20] Available at https://goo.gl/4NhfCZ.

defined hierarchy of drug categories organized to reflect similarities in drug mechanism and disease intended to treat. In that way, it usefully mimics the choice sets faced by physicians. We focus mostly on three measures of prescribing outcomes: the share of a focal drug's claims within (1) all drugs prescribed by the physician that year, (2) all cardiovascular drugs prescribed that year (ATC code = "C"), and (3) all statins prescribed that year (ATC code = "C10AA").

2.1.2 Data on manufacturer payments to providers

Although federally mandated reporting of manufacturer-provider payments did not begin until 2013, nationwide interest in these dealings had been growing for some time. By 2010, states had begun to institute their own payment limitations and/or public reporting rules;[21] a number of high-profile lawsuits found conflicts of interest between physicians and manufacturers to be a punishable offense;[22] and calls from politicians and patient advocacy groups were gaining significant momentum in the press.[23] Amidst this growing concern, a number of pharmaceutical firms, most importantly Pfizer and AstraZeneca, began to publicly release data on payments to physicians, some preemptively, others due to legal settlements. These documents are the basis of our payments data. Because these were internally generated documents, the disclosures came in a wide variety of formats both across firms and within firms over time. In order to account for irregularities in formatting – primarily of names – a machine learning algorithm was developed to create a disambiguated physician-level dataset of payments from Pfizer and AstraZeneca in 2011 and 2012.

Our analyses primarily focus on two variables: (1) a dummy that equals one if a physician is reported to received a general (non-research) payment from a firm in a given year, and (2) the dollar-value reported. As is shown in the summary statistics below (Table 1), the vast majority of these "general" payments are in the form of a meal. Therefore, all analyses will focus only on meals since (1) this is by far the most common type of interaction, and (2) amongst the types of interactions reported, these are the most likely to be related to pure persuasion in contrast to, for example, payments associated with consulting or speaking activities, which are much more likely to be due to services rendered. That is not to say these other forms could not influence physicians; however, our identification strategy is not designed to examine quasi-random variation in these types of interactions.

[21] The District of Columbia, Maine, and West Virginia required disclosure of payments and gifts to physicians prior to our time horizon; Massachusetts, Minnesota, and Vermont required disclosure and had certain statutory gift bans (King and Bearman (2017); Gorlach and Pham-Kanter (2013)).

[22] For example, in 2009 Eli Lilly paid a $1.4 billion fine following allegations of the off-label promotion of its drug Zyprexa (See: https://goo.gl/77xApj). In 2010, Allergan paid a similar fine of $600 million following the illegal promotion of Botox (See: https://goo.gl/g1q1RP).

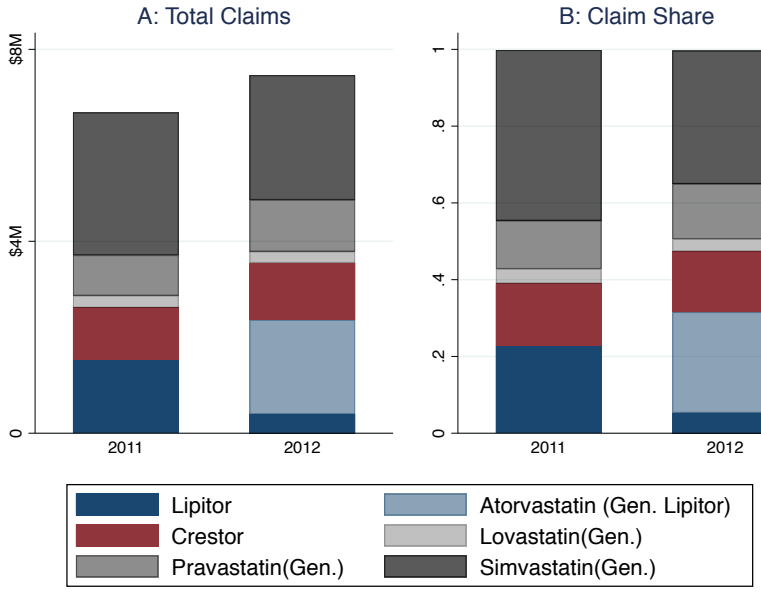
[23] See Senator Chuck Grassley's call for reform here: https://goo.gl/GIPPzF.

2.2 Data Set Construction and Summary Statistics

Starting with the full sample of cardiologists in the Medicare Physician Compare database, per their self-reported primary specialty, we restrict our sample to "active" Medicare prescribers with at least 500 Part D claims in 2010; this is approximately the 10^{th} percentile of claims per physician-year. The final sample used in our analyses contains about 15,000 cardiologists.

To first get a sense of the statin prescribing behavior for this set of cardiologists, Figure 1 plots the total annual number and share of claims for the six major statins (two branded, four generic). Together, these six drugs account for more than 99% of the statin claims and total expenditures in this period.

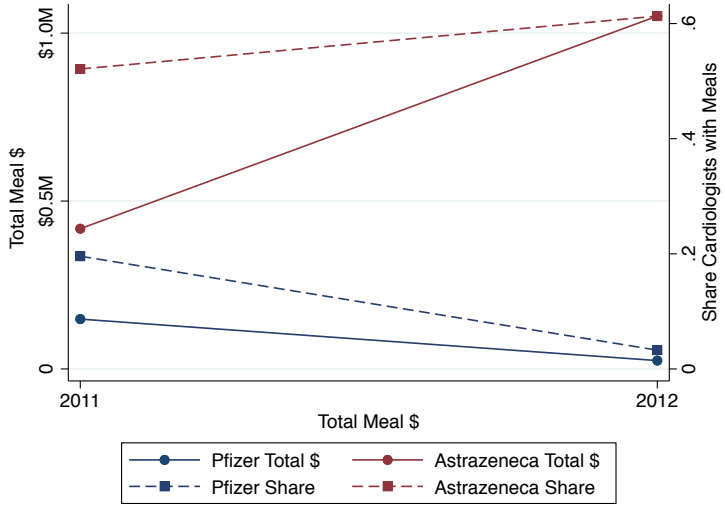
Figure 1: Medicare Part D Cardiologist Statin Market, 2011-2012



Note: Includes the six major statins per Medicare utilization. Drugs denoted "Gen." are the generic versions of those molecules, sold by a large number of different companies. $N_{d,2011} = 14,982$ and $N_{d,2012} = 15,302$.

The entry of generic atorvastatin is clear – in its first full year of availability, this new alternative accounted for roughly 26 percent of statin claims while Lipitor's share dropped from 23 percent in 2011 to about 5 percent in 2012. Figure 2 highlights the trend in meal-related payments during this period where Pfizer reduced its meal rate for cardiologists from roughly 20 percent to 3 percent, while on the other hand AstraZeneca increased both its meal rate and value of meal conditional on receipt.

Figure 2: Firm-wide Meal Expenditures for Cardiologist Sample, 2011-2012



Note: Plots the share of cardiologists included in our sample (N=15,279) that receive a meal from either firm (Right Axis) and the total dollar value of these meals (Left Axis).

Table 1 describes the average payment amounts (all and the meal-related subset) from Pfizer and AstraZeneca, and the claims shares of each firm's statin in our sample of cardiologists. Meal-related payments account for more than 93 percent of these interactions, with the vast majority of these meals being valued at less than $100. The Table also includes the percentiles of the non-zero distributions for each variable, which highlights the extremely skewed nature of payments. It is clear that Pfizer and AstraZeneca implemented different strategies in this timeframe: cardiologists are nearly five times as likely to receive a meal from AstraZeneca compared to Pfizer (62 percent vs. 13 percent), and conditional on receiving a meal, AstraZeneca's median meal value per cardiologist is twice as large ($51 vs. $24). In terms of prescribing behavior, the two focal statins account for a roughly similar share of claims when scaled by total annual claims, or just claims for cardiovascular drugs. However, as evidenced in Figures 1 and 2, these sample averages mask the large changes in prescribing and payments that occurred from 2011 to 2012.

2.3 Identification Strategy – Responsiveness to Meals

Our primary identification strategy exploits variables that shift the costs of interacting with physicians, but which are plausibly exogenous to those physicians' latent preferences over drugs or responsiveness to interactions. The intuition of this approach is that drug firms typically first determine marketing budgets and strategies based on aggregate market characteristics, which we argue are driven by exogenous forces such as local physician capacity

Table 1: Summary Statistics, Focal Firms & Drugs

	Mean	% > 0	Percentiles if > 0					
			10	25	50	75	90	Max
Panel A: Pfizer & Lipitor								
All Non-research $	37.620 (951.311)	0.143 (0.350)	11	13	27	81	155	91125
Meal $	6.942 (34.285)	0.134 (0.341)	11	12	24	57	122	2092
Q. Share, Year	0.024 (0.020)	1.000 (0.000)	.0055	.0094	.0182	.0335	.0517	.2304
Q. Share, Cardio.	0.031 (0.025)	1.000 (0.000)	.0070	.0121	.0233	.04264	.0657	.2589
Panel B: AstraZeneca & Crestor								
All Non-research $	293.430 (3539.037)	0.624 (0.484)	14	25	54	119	205	123175
Meal $	55.283 (117.175)	0.617 (0.486)	14	24	51	110	184	2590
Q. Share, Year	0.026 (0.019)	1.000 (0.000)	.0079	.0127	.0209	.0333	.0496	.2870
Q. Share, Cardio.	0.032 (0.023)	1.000 (0.000)	.0104	.0163	.0266	.0421	.0615	.3072

Note: N=28,962 cardiologist-year observations during 2011-2012. Non-research interactions include, for example, speaking fees, consulting payments, reimbursements for travel, and meals – all payments disclosed by the firm but not explicitly labeled as pertaining to research activities. "Q. Share" are the quantity share of claims for the focal drug (Lipitor/Crestor) as a fraction of the cardiologist's total annual claims (Year), total annual claims for any cardiovascular drug (Cardio.), or total annual claims for any Statin.

overall and by specialty, local population of potential patients, local hospital capacity, and local physician-hospital affiliations. Then the firms' "boots-on-the-ground" representatives use their knowledge of specific physicians to target high-value individuals.

Firms' marketing models can be very detailed and data-driven, relying on strategic plans that factor in the total market size, sales access to physicians, and physicians' responsiveness to inducements. For example, the consulting firm ZS Associates publishes the *Access*

Monitor^{TM} survey, which focuses on characterizing pharmaceutical representative access to physicians. The 2015 *Access Monitor*^{TM} report notes several key factors restricting access: academic medical centers' restrictive access policies, specialty-specific physician employment by hospitals and health systems that have central purchasing or otherwise limit physicians' autonomy, greater competition and productivity pressures on physicians that limit available time for pharmaceutical firm interaction, and so on (Khedkar and Sturgis (2015)).

Given the fixed costs of deploying a sales force to a market, individual physicians' interactions with pharmaceutical firms will experience spillover effects from market-level characteristics. Thus, conditional on variables that proxy for individual physicians' attractiveness to pharmaceutical representatives (which may be correlated with physicians' underlying preferences across drugs or responsiveness), variables that proxy for attractiveness of *other* physicians in the same geographic market represent useful instruments for interactions. As evidence of this "physician-targeting function," consider the 2014 civil case against the DaVita dialysis company. Charges filed on behalf of the US to the District Court of Colorado claimed that DaVita had violated the False Claims Act, and in support of their charges presented internal documents from DaVita that indicated how the company was explicitly choosing to pursue interactions with physicians located in regions with dense populations of patients who could be referred to their dialysis clinics (See Figure 3). In this particular case, the interactions appear to have largely revolved around the prospects of joint venture agreements between physicians and the dialysis clinics. Although this involves a different level of commitment than the $20-50 meals we study here, the underlying premise is clear: firms have access to patient- and physician-level data for their relevant populations and use it to allocate their resources accordingly.

Our identification strategy is intended to address the endogenous selection of physicians into receiving meals based on their patients' diagnoses and preferences, as well as the physicians' own preferences. Carey et al. (2017) address the former source of endogeneity using patients' moving behavior. We note that unobservable differences across physicians – e.g., in their tendency to use branded medications or their responsiveness to meals – will also bias estimated meal effects and estimated welfare implications of a ban on meals. Our strategy is also cross-sectional in nature, meaning that identified "meal effects" may in actuality be proxying for the effects of a long-term sales relationship between a physician-firm pair. We consider this to be appropriate for several reasons. (1) As many researchers have noted, extensive margin effects of payments are large and the evidence on heterogeneity of effects by payment size is mixed (see, e.g., Carey et al. (2017), Yeh et al. (2016), and DeJong et al. (2016)). (2) Our conversations with pharmaceutical marketing specialists and consultants indicate that physician-firm relationships involve repeat interaction by design. This is con-

Figure 3: Physician Targeting Example: DaVita Dialysis Clinics

Note: Internal DaVita documents reveal how the firm utilized data on physicians and patient populations to direct their interactions. Quoting the text of the lawsuit: "The following excerpt from an internal DaVita powerpoint describing the IMS deal shows the precision with which DaVita tracked the potential physician partners' patients and patient locations ... As shown above, in areas where the targeted IMS physicians had patients, DaVita decided to offer a joint venture" – Source: US v. DaVita Inc., and Total Renal Care, Inc., Civil Action No. 09-cv-02175-WJM-KMT.

firmed in our data, in which payments are highly persistent across years. This places our study in contrast to Carey et al. (2017), Mizik et al. (2004), and Datta et al. (2015), in which the researchers include physician fixed effects to take out persistent unobserved differences across physicians. The local average treatment effect of providing one fewer meal to a physician with a long relationship with the given pharmaceutical firm, or of providing the first meal to a physician at the initiation of a physician-firm relationship, may be very different than the average treatment effect of turning an entire relationship on or off. (3) Ideally, one would want to model dynamics in the prescribing effects of meals non-parametrically by randomly allocating physicians to no relationship, frequent meals, and infrequent meals. This is impossible for numerous reasons of cost and practicality, and highlights the difficulty of finding a dataset or quasi-experimental identification strategy that would approximate the ideal.

A traditional econometric approach based on cost shifters would be to choose a single variable to serve as a proxy for shocks to the costs of interaction, assume that the optimal meal level is linear in this proxy, and estimate a two-stage least squares model where meals are instrumented with the proxy. However, there are an enormous number of potential proxies for the costs of interactions and the functional form of how any particular variable influences the optimal interaction level is far from obvious.

Instead, our approach will be to identify a large number of potential instruments that would be observable to firms and useful in predicting the costs of interacting with a particular physician, and then employ LASSO regression to select the final instrument set with most predictive power. In other words, we seek to approximate the function by which firms target their meals to physicians, but only using variables orthogonal to each physician's latent responsiveness.

2.4 Identification Strategy – Price Sensitivity

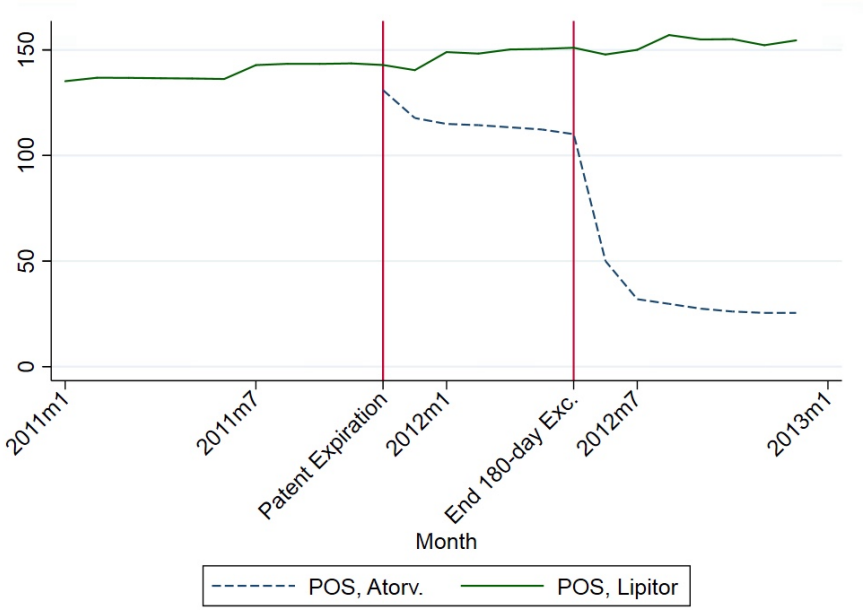
We identify the price sensitivity of demand using panel variation in out-of-pocket prices faced by Medicare enrollees induced by Lipitor's patent expiration. Out-of-pocket prices are generally determined using insurance plan-specific formulas as a function of drug coverage, placement on tiers, point-of-sale price, and benefit phase. If a drug is covered, the out-of-pocket price will be *either* the tier-phase-specific copay *or* the product of the tier-phase-specific coinsurance and the point-of-sale price of the drug. In our analyses, we focus on prices per one-month supply of the relevant drug in the initial coverage phase of the Medicare Part D plan – most claims are filled in the initial coverage phase as opposed to the deductible, donut, or catastrophic phase.

Figure 4 shows the trend in point-of-sale prices for Lipitor and generic atorvastatin over 2011-2012. After Lipitor's patent expired in November 2011, generic atorvastatin was introduced by two generic manufacturers – the "authorized" generic firm Watson Pharmaceuticals and the paragraph IV challenger Ranbaxy Laboratories – that were afforded 180 days of exclusivity from other generic competition. Prices for generics remained high, near $115, for the 180-day generic exclusivity period, then dropped dramatically and leveled out near $25. Branded Lipitor's price remained high, increasing slightly from $135 in early 2011 to $155 during 2012.[24]

Figure 5 below shows the percent of Medicare Part D plans covering atorvastatin and Lipitor during 2011 and 2012. When Lipitor's patent expired in November 2011, there was an immediate jump from about 0 percent to about 80 percent of plans covering atorvastatin. Conversely, the trend downward in plans' coverage of branded Lipitor is much flatter, as many plans did not remove Lipitor from their formularies until well after patent expiration. In fact, as of December 2012, 27 percent of plans still covered Lipitor.

[24]The observed point-of-sale prices are the basis to which enrollees' coinsurances are applied, but they are not net of rebates, and thus do not accurately represent the prices that pharmaceutical manufacturers receive per claim. Rebates are known to be an important strategic variable for branded manufacturers (though not for generic manufacturers). This is one of several reasons we will consider producer surplus aggregated over manufacturers and distributors.

Figure 4: Point-of-Sale Price of Atorvastatin/Lipitor, 2011-2012

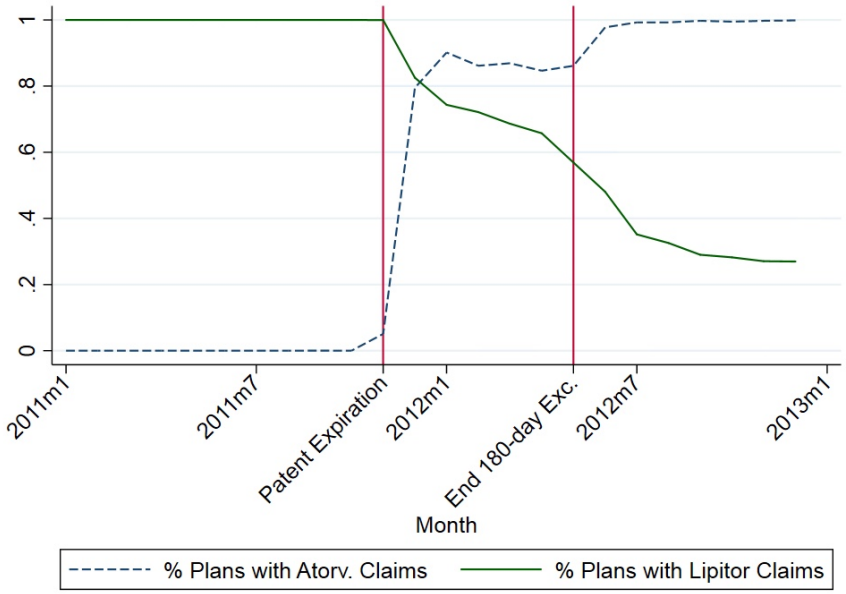


Note: Average point-of-sale price of Lipitor/atorvastatin observed in monthly prescription drug event data. Claims made by non-LIS enrollees for 30-day supply in the initial coverage phase of the drug benefit only.

Figure 6 shows the trend in out-of-pocket prices for Lipitor and atorvastatin in 2011-2012, conditional on Lipitor being on-formulary. Generic copays for atorvastatin drop from about $25 to about $9 after 180-day exclusivity. Lipitor copays are fairly flat, declining from about $38 to $32 over 2011-2012, implying that the primary incentives plans used to induce enrollees to switch from Lipitor to atorvastatin were to drop Lipitor from their formularies and/or reduce copays for atorvastatin.

For our structural model estimation, we use point-of-sale and out-of-pocket prices from the CMS Part D public use files for Q2 2011 and Q3 2012. Prices are collected at the plan-drug-year level. Given that our prescription drug claims data cannot be linked to plans, we aggregate up to the Part D region-drug-year level (Part D regions are supersets of states; there are 39 such regions) using plan enrollment data to construct weighted averages. Cross-sectional variation in prices is generated by plan-pharmacy negotiations over point-of-sale prices and by plan-specific decisions regarding drug coverage and tiering. The coefficients of variation of the point-of-sale (out-of-pocket) price across Part D regions in 2011 were 0.03 (0.18) for Crestor, 0.03 (0.13) for Lipitor, and 0.33 (0.22) for simvastatin. The coefficients of variation for point-of-sale price for Lipitor and Crestor were similar in 2012; however, the coefficient of variation on out-of-pocket price increased to 0.19 for Lipitor, and there was

Figure 5: Coverage of Atorvastatin/Lipitor, 2011-2012



Note: Average formulary coverage of Lipitor/atorvastatin observed in monthly prescription drug event data.

substantial variation in 2012 in terms of both point-of-sale (CV =0.27) and out-of-pocket price (CV =0.28) for generic atorvastatin.[25] This price variation is presented for our focal drugs in Table 2 below.

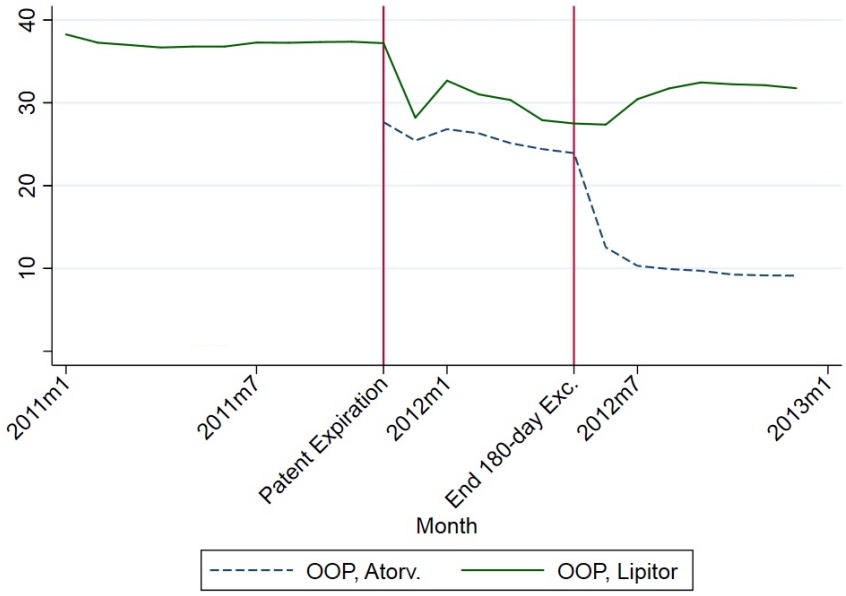
Table 2: Lipitor, Atorvastatin, and Crestor Prices – 2011-2012

		Price 2011					Price 2012					Panel
		Mean	SD	25th	75th	First Stage	Mean	SD	25th	75th	First stage	First Stage w/ Doc FE
Lipitor	OOP	38.10	5.09	34.02	41.16	0.702***	84.21	16.16	77.54	95.01	1.197***	1.265***
	POS	114.92	3.62	113.34	113.86	0.378***	136.21	4.60	134.35	134.83	0.356***	1.210***
Atorvastatin	OOP						11.66	3.23	9.77	11.99	0.839***	
	POS						31.18	8.31	28.51	31.62	1.352***	
Crestor	OOP	40.96	7.28	37.09	45.67	0.932***	38.85	6.89	35.31	41.78	1.109***	0.822***
	POS	138.32	4.15	136.55	137.12	0.360***	161.66	4.93	159.60	160.45	0.312***	1.732***

Many of the determinants of both point-of-sale and out-of-pocket prices across regions at a point in time are likely driven by insurer-specific factors that are correlated across

[25]Note that, as we cannot observe which physicians' claims are for patients with Lipitor on- vs. off-formulary in 2012, we set out-of-pocket price equal to average point-of-sale price in the relevant region when Lipitor is excluded from the formulary. To the extent that some enrollees whose plans dropped Lipitor from the formulary were motivated to purchase Lipitor in cash (in which case the claim would not be recorded in the Medicare Part D data), this will bias our estimates of price sensitivity upward in magnitude.

Figure 6: Out-of-Pocket Price of Atorvastatin/Lipitor, 2011-2012



Note: Average out-of-pocket price of Lipitor/atorvastatin observed in monthly prescription drug event data. Claims made by non-LIS enrollees for 30-day supply in the initial coverage phase of the drug benefit only. patent expiration.

regions. These might include management, contracts with prescription benefit managers, and costs. Given this, we introduce another source of identifying variation – for each plan-drug-region-year, we calculate the average price for that plan-drug-year in *other* regions, and we aggregate that instrument across plans within each region to generate a region-drug-year-specific instrument. The logic is as follows: if (for instance) United HealthCare were particularly slow to remove Lipitor from its formularies, then Lipitor prices in 2012 would be higher in regions dominated by United HealthCare for reasons unrelated to those regions' latent price-sensitivity or willingness to substitute to generic equivalents. The association between the point-of-sale and out-of-pocket prices within and across time is in the "first stage" columns in Table 2. Both within and across years, there is a strong positive association between the pricing policies of the dominant firms in each region and their pricing policies in other regions, even controlling for physician fixed effects in the final column for Lipitor and Crestor.

3 The Effects of Meals on Prescribing

In this Section, we describe our main instrumental variables specifications and results regarding the causal effects of interactions (meals) on prescribing. Our regression specifications rely on a large number of potential instruments and covariates that would be observable and used by firms to predict the costs and benefits of interacting with a particular physician. We employ the methods outlined by Belloni et al. (2012), Belloni et al. (2014), and Chernozhukov et al. (2017), wherein LASSO regressions are used select the most relevant subset of these variables. We seek to approximate the function by which firms target their meals to physicians, only using variables that are expected to be orthogonal to each physician's preferences and latent responsiveness conditional on relevant covariates.

The main regressions and underlying assumptions are of the form:

$$Y_{jd} = \theta 1_{\{m_{jd}>0\}} + f_j(\mathbf{X_{jd}}) + \epsilon_{jd}, \quad \mathbb{E}[\epsilon|\mathbf{X},\mathbf{Z}] = 0, \tag{1a}$$

$$1_{\{m_{jd}\}>0} = g_j(\mathbf{X_{jd}}) + h_j(\mathbf{Z_{jd}}) + \mu_{jd}, \quad \mathbb{E}[\mu|\mathbf{X},\mathbf{Z}] = 0 \tag{1b}$$

where the utilization outcome Y for a cardiologist d and molecule j depends on whether or not the molecule's manufacturer provides payment to the cardiologist (i.e., in the form of a meal; $1_{\{m_{jd}\}>0} = 1$), given a function of covariates $\mathbf{X}$ that proxies for heterogeneity in physicians' patient populations and other preference-relevant factors. We estimate these regressions separately in 2011 and 2012 given the entry of generic atorvastatin. We allow the role of these variables to be drug-specific (and, accordingly, firm-specific), capturing the fact that certain physicians are likely more valuable to certain firms (e.g., due to the types of patients they treat across all product lines they produce). The focal parameter θ describes the effect of industry interaction on the physician's treatment decisions. Since these interactions do not randomly occur, we are concerned that simple OLS regressions of Eq. 1a will over- or underestimate θ, which motivates the instrumental variable approach using $\mathbf{Z}$. The terms $g_j(\mathbf{X_{jd}})$ and $h_j(\mathbf{Z_{jd}})$ in Eq. 1b represent, respectively, a physician-specific targeting function that may be correlated with preferences, and an exogenous targeting function of market-level variables.

We operationalize $\mathbf{X}$ and $\mathbf{Z}$ with a large vector of observables, detailed below. Following Belloni et al. (2012), Belloni et al. (2014), and Chernozhukov et al. (2017), we use the following procedure. First, we use a LASSO regression of Y on $\mathbf{X}$ to select included covariates. Second, we use a LASSO regression of $1_{\{m_{jd}\}>0}$ on $\mathbf{X}$ and $\mathbf{Z}$ to select additional covariates and instruments. Third, we estimate Eq. 1a using 2SLS, including all covariates $\overline{\mathbf{X}} \subset \mathbf{X}$ from the first and second steps and instrumenting for $1_{\{m_{jd}\}>0}$ using $\hat{h}_j(\overline{\mathbf{Z}}_{\mathbf{jd}})$ from the second

step. All variable selection, and the generation of the index $\hat{h}_j(\overline{\mathbf{Z}}_{\mathbf{jd}})$, are performed on one sample and then estimation is performed on another sample, following the double/debiased approach of Chernozhukov et al. (2017).

3.1 Potential Instrument Set

Table 3 below outlines the sets of variables and transformations thereof included in our estimation procedure. To summarize, we include two major sets of variables: (1) "utilization" variables capture the number of patients a physician treats with certain types of drugs; and (2) "features" variables, which describe a wide range of characteristics related to the size and types of organizations, as well as the insurance and health status of populations. Together, these variables form the basis of our approximation to the functions $f(.)$, $g(.)$, and $h(.)$ above. We generate these variables for four main levels of observation: individuals, hospitals, HSAs, and HRRs, with each unit subsuming the last. We classify all individual-level variables as covariates $\mathbf{X}$. We classify variables in the aggregated levels based on whether or not they are arguably exogenous features of a market ($\mathbf{Z}$s) or are likely correlated with certain types of physicians and their responsiveness to industry interaction ($\mathbf{X}$s).

We identify each physician's drug-class-specific claims volumes using the 2010 Medicare Part D claims data. Using the full sample of Medicare physicians (including all specialties), we construct average volume metrics at three levels of ATC drug classes: Cardiovascular, Lipid-Modifiers, and Statins. These ATC drug classes correspond to where statins sit in the ATC hierarchy – statins are a subset of lipid-modifiers, which are a subset of cardiovascular drugs.

The volume metrics are calculated at four levels of observation (Hospital Referral Region (HRR); Hospital Service Area (HSA); Hospital; and Individual) and separately for cardiologists and all other specialties. The HRR-, HSA-, and Hospital-level metrics are calculated using jack-knife procedures in which each physician is excluded from the Hospital-level measures; each physician's hospital is excluded from the HSA-level measures; and each physician's HSA is excluded from the HRR-level measures. Thus, for example, an HRR-level metric for cardiologist i would indicate the average annual number of cardiovascular drug claims for a physician in i's HRR, but *not* in i's HSA. This procedure is an effort to minimize the degree of collinearity across the set of metrics, and is intended to mimic a firm's marketing spend targeting procedure, wherein resources are allocated to regions, hospitals, and physicians with larger patient pools at risk of using the firm's drug.

We supplement the HRR volume metrics with data from the Behavioral Risk Factor Surveillance System (BRFSS). Using the 2011 BRFSS we identify three additional HRR-

Table 3: Overview of Potential Covariate and Instrument Sets

Panel A: Initial Potential Covariates (X)		
Level of Obs.	Utilization	Features
Cardiologist	2010 Claims, Statins[1]	Num. Practice Zip Codes[1]
	2010 Claims, Cardiovascular	Num. Hospital Affiliations[1]
	2010 Claims, Total	Num. Practice Affiliations[1]
		Num. Specialties[1]
		Is AAMC Faculty[2]
		If Faculty, AMSA Score Absolute & Relative[2]
Hospital		Num. AAMC Affils.[2]
		Num. AAMC Faculty[2]
		Share Doc. AAMC Faculty[2]
		Avg. AMSA Score of Faculty[2]
		Avg. AMSA Score, Share Weighted[2]
HSA / HRR		Medicare Advantage, Num. Eligible[3]
		Medicare Advantage, % Covered[3]
		Population, % Uninsured[4]
		Population, % on Medicaid[4]

Panel B: Initial Potential Instruments (Z)		
Level of Obs.	Utilization	Features
Hospital	Per-(Doc./Cardio.) Avg. 2010 Claims, Statins	Num. Beds[5]
	Per-(Doc./Cardio.) Avg. 2010 Claims, Cardio.	Num. Admissions[5]
	Per-(Doc./Cardio.) Avg. 2010 Claims, Total	Num. Practices Affiliated[1]
	Sum (Doc./Cardio.) 2010 Claims, Statins	Num. Cardio. & Doc. Affiliated[1]
	Sum (Doc./Cardio.) 2010 Claims, Cardio.	
	Sum (Doc./Cardio.) 2010 Claims, Total	
H.S.A, H.R.R.	Per-(Doc./Cardio.) Avg. 2010 Claims, Statins	Num. Cardio. & Doc[1]
	Per-(Doc./Cardio.) Avg. 2010 Claims, Cardio.	Num. AAMCs[2]
	Per-(Doc./Cardio.) Avg. 2010 Claims, Total	Num. AAMC Faculty[2]
	Sum (Doc./Cardio.) 2010 Claims, Statins	Teaching Hospitals Share of Admissions & Beds[5]
	Sum (Doc./Cardio.) 2010 Claims, Cardio.	
	Sum (Doc./Cardio.) 2010 Claims, Total	Medicare Population, Cardiac Hospitalization Rate[4]
	Per-(Doc./Cardio.) Avg. 2010 Claims, Firm-Other, ATC-1	
	Per-(Doc./Cardio.) Avg. 2010 Claims, Firm-Other, ATC-5	
	Sum (Doc./Cardio.) 2010 Claims, Firm-Other, ATC-1	
	Sum (Doc./Cardio.) 2010 Claims, Firm-Other, ATC-5	

Note: "Per-(Doc./Cardio.)" indicates that the variable is calculated for both all physicians and just cardiologists. The "Firm-Other" versions of claim counts consider drugs in any Anatomical Therapeutic Chemical Classification System class that the focal firm manufactures a drug in, except for Lipitor or Crestor. ATC-1 and -5 refer to the 1-digit and 5-digit levels of the ATC hierarchy (e.g., "C" for Cardiovascular system and "C10AA" for HMG CoA reductase inhibitors.

Data sources as follows:

[1] CMS Part D Public Use Files & CMS Physician Compare Data; applicable to all claims data

[2] American Academic Medical Center Faculty Roster & American Medical Student Association Conflict of Interest Report Card

[3] CMS Medicare Advantage enrollment and landscape files

[4] Behavioral Risk Factor Surveillance Survey

[5] American Hospital Association Annual Survey

specific variables: (1) the average rate of cardiovascular-related hospitalizations for Medicare beneficiaries, (2) the uninsurance rate, and (3) the percent of individuals enrolled in Medicaid. Together these variables likely capture first-order variation in disease prevalence, health insurance coverage, and incomes.

In an attempt to introduce additional proxies for the costs of physician interactions, we identify a number of affiliation and density related metrics. Our identification is essentially based on returns to scale in marketing – when there are many attractive hospitals or physicians clustered geographically, fixed costs to the firm of setting up a meals program can be spread over more interactions. We construct a set of "attribute" variables at the three levels of observation as follows: (1) HRR and HSA: number of cardiologist and doctors, number of academic medical centers and associated faculty, and teaching hospitals' local share of admissions; (2) Hospital: number of beds, number of admissions, number of affiliated physician practices, and number of cardiologists and physicians affiliated; and (3) Individual: number of practice locations, number of hospital and practice affiliations, number of specialties, and so on. Again, higher-level aggregations are jack-knifed.

As indicated in Table 3, our controls focus on proxies for physicians' latent preferences (past utilization), patient population size and complexity (affiliations and number of specialties), access restrictions (affiliations with Academic Medical Centers and rating of affiliated AMCs' conflict-of-interest policies from the American Medical Student Association (AMSA)), and local price-sensitivity (managed care penetration, population uninsured, population on Medicaid). Our potential instruments instead focus on *other physicians'* preferences and patient populations and other measures of local hospital capacity.

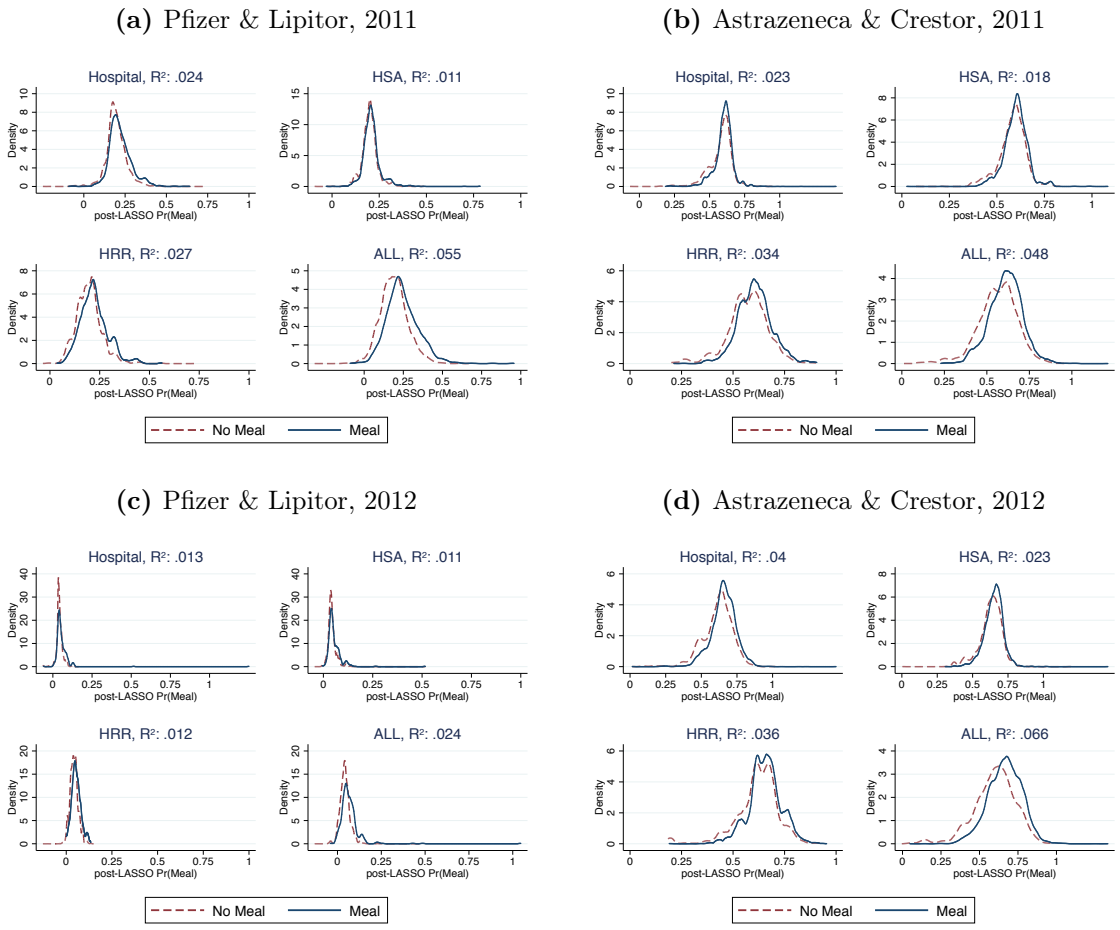
Beginning with these raw volume and attribute variables, we introduce a number of transformations and interactions: (1) percentiles (National for HRRs; HRR for Hospitals; Hospital for individuals); (2) jack-knife counts of individuals above the national median; (3) squared terms; (4) volume-attribute interactions using the same level of observation (i.e. interacting all HRR-level volume metrics with all HRR-level attribute metrics). The final set includes 63 control variables (of 85 possible) and 123 instruments (of 438 possible) for Lipitor in 2011.

3.2 Instrument Selection Results

Figure 7 shows the performance of the different levels of potential instrument sets. It shows the distribution of predictions by the LASSO-selected instruments after conditioning out variation due to the LASSO-selected controls, split by whether the relevant cardiologist-year did receive a meal from the firm's manufacturer. The predicted meal probability distribution

is shifted upward for cardiologists that received meals; the richest instrument set can explain roughly 5-7 percent of the residual cross-sectional variation in meals. The Hospital- and HRR-level instruments contribute more identifying variation than the HSA-level instruments. Thus, it appears we are capturing important sources of variation in meal payments.

Figure 7: Instrument Performance, by Sample & Level of Observation



Note: Displays the distribution of post-LASSO predicted meal probabilities based on instruments only, after conditioning out controls, split by realized outcome.

Our goal in using the instruments we identify and the LASSO approach to selection is to approximate the latent average cost of interacting with any particular physician given their surroundings. Our local average treatment effect (LATE) will be identified off of compliers: physicians that are selected into meals due to spillovers from their environment. Our results may not generalize to physicians that would never receive payments (e.g., due to low latent value or physician-specific access restrictions) or to physicians that would always receive payments (e.g., due to high latent value or physician-specific ease of access).

3.3 Results

In this Section, we estimate Eq. 1a, where our focal outcome ($log(Claims)$ for each cardiologist-drug-year) depends on whether or not the firm who manufactures the drug provided payment to the cardiologist (i.e. in the form of a meal), conditional on a high-dimensional set of controls $\overline{\mathbf{X}}$. The focal parameter θ describes the effect of industry interaction on the physicians' treatment decisions.

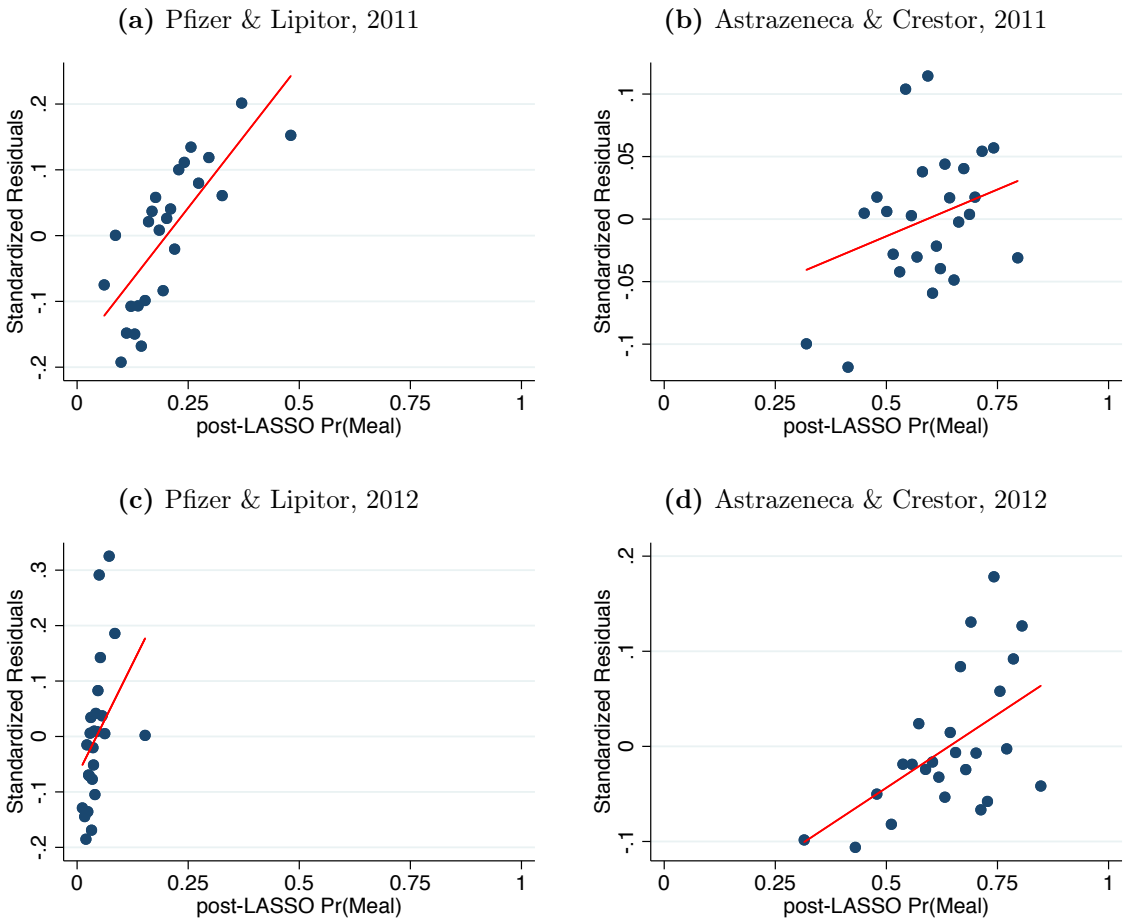
Because these interactions do not randomly occur, we are concerned that the receipt of a payment is correlated with the error term. Depending on the direction and magnitude of this correlation, simple OLS regressions of Equation 1a will over- or under-estimate the true causal payment treatment effect, which motivates the instrumental variable approach described previously. We might expect OLS results to be biased up or down: firms may attempt to persuade physicians with inherently larger or smaller relative utilization. Note that the degree of this bias will depend on the shape of what one might call the "persuasion function" as it varies across the outcome distribution. I.e., low-volume physicians may be more or less persuadable than high-volume physicians: low-volume cardiologists may have less information about product substitutes, but high-volume cardiologists may have greater affinity with representatives of cardiovascular drug firms.

Table 4: First Stage & Reduced Form

	Pre: 2011		Post: 2012	
	Any Meal	log(Claims)	Any Meal	log(Claims)
Panel A: Lipitor & Pfizer				
post-LASSO $\widehat{\mathbf{Z}_d}$	1.072***	0.583***	1.101***	1.672***
	(0.0633)	(0.103)	(0.117)	(0.357)
N	14378	14378	10598	10598
Mean Dep. Var.	0.201	103.8	0.0438	37.62
Panel B: Crestor & Astrazeneca				
post-LASSO $\widehat{\mathbf{Z}_d}$	1.108***	0.101	1.160***	0.318***
	(0.0574)	(0.0852)	(0.0537)	(0.0849)
N	12999	12999	13562	13562
Mean Dep. Var.	0.592	83.42	0.642	87.52

Figure 8 presents the reduced form relationship between our approximation of Pfizer's and Crestor's targeting functions and realized $log(Claims)$ in each period, after conditioning out controls. Here, we observe a positive relationship between the *Post-LASSO Pr(Meal)* instrument and prescribing for each drug-year. This relationship is steeper for Lipitor in both years, and steeper for Crestor in 2012 than in 2011. The former may be related Pfizer

Figure 8: Reduced Form, $log(Claims)$



Note: Binned scatterplots of standardized residuals of $log(Claims)$ as a function of the post-LASSO predicted meal probabilities, after controlling for the LASSO-selected covariates.

focusing its payments on physicians in markets with the highest predicted response in 2011 and 2012, late in Lipitor's life cycle. The latter would be consistent with business stealing between Pfizer and AstraZeneca prior to Lipitor's patent expiration.

Table 4 reproduces the Figure using regressions and includes the first stage as well. In this Table and the OLS and 2SLS results below, we restrict to cardiologist-years in which claims are nonzero in order to facilitate comparison with our structural results.[26] By construction, the first stage coefficient is close to one for all specifications, as it is generated as an index of all instruments selected by the LASSO. The reduced form effects of payments is large in relative terms for both Lipitor and Crestor. Consistent with the steep patterns in the Figure

[26]This restriction is not material for 2011 or for Crestor in 2012, but does have a larger effect on the sample for Lipitor in 2012.

above, a 100 percent increase in the predicted meal likelihood increases Lipitor claims by 50 percent in 2011 and by 167 percent in 2012 (the latter effect is relative to a much smaller baseline of only 38 claims, vs. 104 claims in 2011). The Crestor effects are much smaller, indicating a 10-32 percent increase in claims from a baseline of about 85.

Table 5 presents the naive results of estimating Equation 1a via OLS with and without post-LASSO controls, alongside the 2SLS estimates. The Table presents results for the focal statin-year's $log(Claims)$, as in the above. Consider first the "Pre-OLS" estimates that identify the correlation between Pfizer meal receipt and Lipitor claims in 2011. The coefficient of 0.445 indicates that physicians receiving a meal from Pfizer in 2011 had about 45 percent greater Lipitor claims; however, when we include controls for physician type, the OLS coefficient drops to 0.154. It appears that physician characteristics are important determinants of both meal receipt and prescribing. The 2SLS estimate for this same sample identifies a treatment effect nearly four times larger, where a meal increases Lipitor's claims by 55 percent. Examining AstraZeneca in this same period, the OLS and 2SLS estimates are very similar once controls are included, implying that a meal increases Crestor claims by roughly 9 percent (though the 2SLS effect is not significant).

Table 5: OLS v 2SLS, y=log(Claims)

		Pre			Post	
	OLS	OLS	2SLS	OLS	OLS	2SLS
Panel A: Lipitor & Pfizer						
Any Meal	0.445***	0.154***	0.553***	0.359***	0.155***	1.365***
	(0.0210)	(0.0142)	(0.0934)	(0.0423)	(0.0324)	(0.347)
N	14378	14378	14378	10598	10598	10598
post-LASSO Controls		Y	Y		Y	Y
Mean Dep. Var.	103.8	103.8	103.8	37.62	37.62	37.62
F-stat			285.9			79.42
Panel B: Crestor & Astrazeneca						
Any Meal	0.297***	0.151***	0.0949	0.268***	0.148***	0.230***
	(0.0177)	(0.0130)	(0.0771)	(0.0178)	(0.0137)	(0.0731)
N	12999	12999	12999	13562	13562	13562
post-LASSO Controls		Y	Y		Y	Y
Mean Dep. Var.	83.42	83.42	83.42	87.52	87.52	87.52
F-stat			336.5			447.2

A similar pattern emerges when examining 2012, except that the relative difference between the OLS and 2SLS estimates is more dramatic, especially for Pfizer/Lipitor where the difference between the coefficients is nearly an order of magnitude. The 2SLS effect of meals on Crestor prescribing is about 23 percent, vs. an OLS estimate of 15 percent.

Our general finding of larger positive 2SLS meal effects suggests that both Pfizer and AstraZeneca provide meals to a large number of physicians that are only slightly higher-than-average prescribers of Lipitor/Crestor at baseline, but that are highly responsive to meals. The larger results in 2012 are consistent with a strategy whereby Pfizer dramatically reduces Lipitor-related meals to cardiologists after Lipitor's patent expires, leaving only physicians in the most attractive (persuadable) markets (i.e., cardiologists with a large θ^m). Thus, the difference in 2011 and 2012 estimates for Pfizer suggests a great deal of heterogeneity in meal treatment effects. In contrast, the AstraZeneca IV-identified meal treatment effect is only slightly larger in 2012, indicating that the generic entry of atorvastatin only slightly altered AstraZeneca's ability to influence physicians' use of Crestor.

3.4 I.V. Robustness & Selection

Here, we examine robustness of our findings along several dimensions. First, we generate an instrument index that utilizes only the HSA- and HRR-level variables and re-estimate the 2SLS models omitting physicians' own affiliated hospitals. The variables most likely to fail the exclusion restriction are those that are "closer" to the individual physician level. If this is in fact the case, then utilizing only the HSA- and HRR-level variables (which do not include any physician-specific data) should identify smaller point estimates. Table 6 compares our baseline results for Pfizer/Lipitor 2011 to 2SLS results excluding Hospital-level instruments.

Table 6: Pfizer & Lipitor 2011, *log*(Claims), Meal Effect by Instrument Variable Groups

	(1)	(2)
Any Meal	0.920***	0.665***
	(0.134)	(0.114)
N	14378	14378
Mean Dep. Var.	103.8	103.8
F-stat	265.1	86.15
Instrument Split	All IVs	Without Hospital IVs

Next, because we can observe the dollar value associated with these meals, we can examine the extent to which effects are driven differentially by the extensive or intensive margins of interactions. Focusing just on Pfizer and Lipitor, Table 7 presents coefficients when restricting the sample to different maximum payment amounts at the 25th, 50th, 75th, and 90th percentiles of the *non-zero* meal value distribution.

Clearly, the extensive margin effect of receiving any meal leads to a larger absolute and relative increase in claims for Lipitor. As larger and larger meal values are included in the

Table 7: Pfizer & Lipitor 2011, *log*(Claims), Meal Effect by Dollar Values

	(1)	(2)	(3)	(4)
Any Meal	1.295***	0.726***	0.612***	0.549***
	(0.329)	(0.162)	(0.117)	(0.100)
N	12228	12957	13660	14093
Mean Dep. Var.	95.63	97.71	100.4	101.9
F-stat	55.51	115.8	184.3	253.0
Meal $ P.tile $\leq$	25th	50th	75th	90th
Meal $ $\leq$	12	24	56	120

sample, the apparent returns to the marginal dollar decrease dramatically. Thus, it appears that the vast majority of the effect is driven by the receipt of any meal, regardless of its value. It is not surprising then that the vast majority of meal values we observe are less than $100. For this reason, in the structural analyses below we will simply focus on the dummy variable indicating any meal receipt.

When combined with the prior comparison of OLS and 2SLS results, this apparently large role of the extensive margin effect has important implications for the policy discussions surrounding physician-firm interactions. Our results would indicate limited practical effects of policies focused on limiting high-value meals (e.g., over $50) or high-upper-tail prescribing behavior. Firms seem to have great influence over what otherwise would have moderate-volume prescribers, and this influence is largely driven by interactions involving a low-valued meal.

4 Welfare Analysis Using Supply and Demand Model

The goal of this Section is to motivate our identification strategy, and to present a model of supply and demand that allows us to: (1) disentangle own molecule and competitor molecule effects, and (2) compute counterfactual prices and quantities to better understand the welfare effects of industry interactions with physicians.

4.1 Model: Demand, Supply, and Endogenous Interactions

The utility of molecule $j \in \mathcal{J} = \{1, ..., J\}$ (b denoting branded or generic version) for use case i (a doctor/patient/visit combination) under doctor d in year t is

$$u_{ijbdt} = \delta_{jbdt} + \varepsilon_{ijbdt}. \tag{2}$$

The use-specific i.i.d. unobservable $\varepsilon_{ijbdt} = \epsilon_{igdt} + (1-\lambda^g)\epsilon_{ijbdt}$ is the random coefficients representation (from Cardell (1997)) of the nested logit model where ϵ_{igdt} is a random component common to group g; and ϵ_{ijbdt} is the standard type I extreme value error term (with scale normalized to one). As the nesting parameter $\lambda^g \in [0,1]$ approaches 1, there is less substitution outside the nest. The outside good is non-statin cardiovascular drugs, including other lipid-modifying drugs. Our preferred specification nests strong statins (atorvastatin/Lipitor and rosuvastatin/Crestor) in one group (with nesting parameter λ^{ss}) and the other, moderate, statins in another (λ^{ms}). All moderate statins were generic during our time horizon.

The mean utility across use cases is specified as

$$\delta_{jbdt} = \theta^m 1_{\{m_{jbdt}>0\}} - \theta^p p_{jbdt} + \theta_j + \theta_t + f_j(X_{jbdt}) + \xi_{jbdt}, \tag{3}$$

where $\theta^m 1_{\{m_{jbdt}>0\}}$ is an indicator for whether provider d received a meal from the manufacturer of branded molecule $j^{b=1}$ and its weight; and $\theta^p p_{jbdt}$ is the average price paid by patients and its utility weight; θ_j are molecule specific dummy variables and their utility weights; θ_t are year-specific dummy variables and their utility weights to capture general market trends; $f_j(X_{jbdt})$ is the product-specific linear function of LASSO double-selected X variables to capture regional variation in prescribing patterns; and ξ^{jbdt} is a product-physician-year unobservable preference heterogeneity term.

Given a set of products $\mathcal{J}_t$ and flow of choice opportunities Q_{dt}, we assume the provider/patient chooses the product that maximizes utility for each use opportunity, so that quantities demanded are given by:

$$q_{jbdt} = Q_{dt} Pr[u_{ijbdt} > u_{ikb'dt}, \forall kb' \in \mathcal{J}_t] = Q_{dt} \frac{e^{\frac{\delta_{jbdt}}{1-\lambda^g}}}{\sum_{kb' \in \mathcal{J}_{gt}} e^{\frac{\delta_{kb'dt}}{1-\lambda^g}}} \frac{\left(\sum_{kb' \in \mathcal{J}_{gt}} e^{\frac{\delta_{kb'dt}}{1-\lambda^g}}\right)^{1-\lambda^g}}{1 + \sum_{h \in \{ms,ss\}} \left(\sum_{kb' \in \mathcal{J}_{ht}} e^{\frac{\delta_{kb'dt}}{1-\lambda^h}}\right)^{1-\lambda^h}}, \tag{4}$$

and consumer surplus across all products is given by:

$$CS_{dt}(\mathcal{J}_t) = Q_{dt} \frac{1}{\theta^p} \ln \left(1 + \sum_g \left(\sum_{jb \in \mathcal{J}_{gt}} e^{\frac{\delta_{jbdt}}{1-\lambda^g}} \right)^{1-\lambda^g} \right) - \sum_{jb \in \mathcal{J}_t} q_{jbdt} \left(\frac{\theta^m}{\theta^p} 1_{\{m_{jbdt}>0\}} \right), \tag{5}$$

which is the standard formula derived by McFadden (1978), minus an adjustment for the fact that potential bias due to meals affects decisions, but not utility directly. An equivalent interpretation would be that physicians maximize a sum of physician (chooser) and patient (consumer) utility, that all terms but $\theta^m 1_{\{m_{jbdt}>0\}}$ represent consumer utility.

We next characterize how prices and meals are determined in equilibrium. In the foregoing, the lack of a d subscript on price indicates that all prices are held fixed across providers in each market. Let the supplier's profit function be given by:

$$\pi(p^{pos}_{jbt}, m_{jbdt}) = \sum_d \left(q_{jbdt}(p^{pos}_{jbt} - mc_{jbt}) - (\bar{m} + c^m_{dt}) 1_{\{m_{jbdt}>0\}} \right) \tag{6}$$

where mc_{jbt} is a function capturing the costs of manufacturing and distributing the marginal unit of molecule j, $\bar{m}$ is the fixed and exogenous cost of a meal, and c^m_{dt} captures the fixed cost of interacting with physician d (roughly equivalent to a "marketing" cost over and above the dollar value of the meal). We assume that prices of the substitute drugs in the market are determined in a Nash Equilibrium of Nash Bargaining between suppliers (manufacturers/wholesalers/pharmacies) and buyers (PBMs/insurers). This captures the primary forces relevant to our research question, abstracting from some of the details of the upstream interactions between manufacturers/wholesalers/pharmacies, and from insurer competition and tiering/formulary details. In the model, each price maximizes the Nash Product of the gains from trade for each supplier and buyer pair, taking other prices as given. We assume that meals and prices are determined simultaneously. The first-order condition on each price is (here $q_{jbt} := \sum_d q_{jbdt}$ denotes the sum over physicians):

$$\begin{aligned} p_{jbt} &= \arg\max \left(\pi(p^{pos}_{jbt}, p^{oop}_{jbt}, m_{jbdt}) \right)^{b_{jbt}} \left(\frac{\widetilde{CS}_t(\mathcal{J}_t) - \widetilde{CS}_t(\mathcal{J}_t \setminus jb)}{q_{jbt}} \right)^{1-b_{jbt}} \\ &= mc_{jbt} + b_{jbt} \left[\left(1 + \frac{\partial q_{jbt}}{\partial p^{oop}_{jbt}} \frac{p^{oop}_{jbt} - mc_{jbt}}{q_{jbt}} \right) \frac{\widetilde{CS}_t(\mathcal{J}_t) - \widetilde{CS}_t(\mathcal{J}_t \setminus jb)}{q_{jbt}} + p^{pos}_{jbt} - mc_{jbt} \right] \end{aligned} \tag{7}$$

Here, the term $b_{jbt} = \beta_{jb}\nu_{jbt}$ is a bargaining ability parameter, weighting the extent to which the optimal price depends on supplier profits vs. the expected additional buyer surplus in the case that a contract is agreed to for product jb: $\widetilde{CS}_t(\mathcal{J}_t) - \widetilde{CS}_t(\mathcal{J}_t \setminus jb)$. Note the model captures the important feature of health insurance negotiations that quantities and thus elasticities are driven by physician and consumer decision-making based on out-of-pocket price under insurance coverage p^{oop}, but the insurer and supplier negotiate over point of sale price p^{pos}. In contrast to some papers in the bargaining literature (e.g., Gowrisankaran et al. (2015), Grennan (2013), Ho and Lee (2017)), we do not model negotiations for the prices of the full bundle of products consumed by insurance plan enrollees; in particular, we do not observe how plan enrollment might respond to disagreement. We proxy for the plan's potential surplus by subtracting plan insured costs from the insured physician/consumer surplus (i.e., insured willingness-to-pay). Thus, the buyer surplus term differs from consumer surplus $\widetilde{CS}_t(\mathcal{J}_t) := CS_t(\mathcal{J}_t) - \sum_{jb} q_{jbt}(p^{pos}_{jbt} - p^{oop}_{jbt})$. We link negotiated point-of-sale price and out-of-pocket price via an exogenously specified cost-sharing parameter $p^{oop}_{jbt} = cs_{jbt} p^{pos}_{jbt}$.[27]

[27] One potential caveat to this approach is that we do not observe confidential rebates between plans

The first-order condition on meals will be:

$$m^*_{jbdt} > 0 \quad \Leftrightarrow \quad (q_{jbdt,\{m_{jbdt}>0\}} - q_{jbdt,\{m_{jbdt}=0\}})(p^{pos}_{jbt} - mc_{jbt}) > \bar{m} + c^m_{dt}. \tag{8}$$

Firms give meals to any physician when the meal-induced shift in revenues is greater than the total costs of interacting with that physician.

Intuitively, the implications of our model, in which prices and interactions are jointly determined and demand depends on both, can be summarized as follows:

- The quantity consumed of the drug will depend on the availability of generic substitutes, relative prices, and meals.
- The marginal return to meals m^* for a given doctor will depend on the provider's panel size Q_{dt}, their responsiveness $q_{jbdt,\{m_{jbdt}>0\}} - q_{jbdt,\{m_{jbdt}=0\}}$, and the unit margin $p^{pos}_{jbt} - mc_{jbt}$.
- For reasonable parameters, generic entry will decrease the marginal return to meals, though there are parameter combinations for which generic entry *increases* the marginal return to meals.
- The likelihood of a physician receiving meals will depend on the marginal return for that physician, but also on the physician-specific marginal cost of interaction c^m_{dt}. For example, if there are lower costs of interacting with physicians that are geographically close to the firm's headquarters, or of interacting with physicians in large practices, then physicians' propensity to receive meals will vary in geographic space and in practice size.

4.2 Identification and Estimation

We follow the procedure in Berry (1994), setting choice probabilities implied by the demand model equal to market shares observed in the data, and inverting the system to yield a linear correspondence between a function of market shares and the mean utility for each product $\ln(s_{jbdt}/s_{0dt}) - \lambda^g \ln(s_{jb|_g dt}) = \delta_{jbdt}$, leading to the linear estimation problem:

$$\ln(s_{jbdt}/s_{0dt}) = \lambda^{g_j} \ln(s_{jb|_g dt}) + \theta^m 1_{\{m_{jbdt}>0\}} - \theta^p p_{jbdt} + \theta_j + \theta_t + f_j(X_{jbdt}) + \xi_{jbdt}. \tag{9}$$

and manufacturers. To the extent that realized net-of-rebate prices to plans are much lower than observed point-of-sale prices for branded pharmaceuticals, our estimates of b would be biased upward. We cannot non-parametrically identify a separate term for b and rebates and our theory does not suggest clearly how a ban on meals would impact rebates. Thus, our counterfactual analyses implicitly hold both rebates and b fixed.

Estimating this equation faces two well-known challenges in that theory suggests $\ln(s_{jb|gdt})$, p_{jbdt}, and $1_{\{m_{jbdt}>0\}}$ are all correlated with the unobservable term ξ_{jbdt}. We take an instrumental variables approach to solving this identification problem, leveraging the variation induced by the introduction of generic atorvastatin and the regional variation in prices and choice sets introduced by timing of formulary changes across Medicare Part D carriers.

To use the variation induced by the introduction of generic atorvastatin to the choice set, we follow the suggestion of Gandhi and Houde (2016), constructing an instrument that interacts the post-entry period with indicators for Lipitor and strong statins (Lipitor and Crestor), $Z^a = [1_{\{t=2012\}} \cdot 1_{\{jb=Lipitor\}}, 1_{\{t=2012\}} \cdot 1_{\{jb\in\mathcal{J}_{ss}\}}]$. With our molecule and time fixed effects, this instrument captures difference-in-differences variation, allowing the effect of the treatment on substitution patterns to differ by whether a drug is a moderate statin (absorbed in the time trend), a strong statin (the group most closely related to atorvastatin in product space), or Lipitor (branded atorvastatin–the same molecule). These instruments help identify substitution patterns broadly, and in theory are valid for both $\ln(s_{|_g})$ and p.

We further leverage the heterogeneity in insurer responses to atorvastatin entry across geography, as described in Section 2.4. Some insurers instantly added generic atorvastatin to their preferred drug list and/or removed Lipitor from their formulary, while others took more than a year. The variation in penetration of these insurers across geography generates variation in the relative prices consumers faced. To utilize this variation, we create instruments for each plan-drug-year-region as the average price for that drug-year-insurer across *other* regions. We then average across plans to create an instrument for physician d's region: $Z^p = [p^{IV}_{jbdt}]$. These are similar to the bargaining ability instruments in Grennan (2013, 2014), with the added benefit of a clear mechanism driving them. As such, they are also valid for both $\ln(s_{|_g})$ and p.

In addition to the instruments linked to generic atorvastatin entry, we also follow much of the literature (e.g., Berry and Waldfogel (1999)) in using a polynomial in the size of the set of moderate statins prescribed $Z^J = [1/|\mathcal{J}^{ms}_{dt}|, |\mathcal{J}^{ms}_{dt}|, |\mathcal{J}^{ms}_{dt}|^2]$ as an instrument. This leverages the fact that more variety will mechanically affect within group shares.[28]

Finally, our instrumental variables strategy for meals $1_{\{m_{jbdt}>0\}}$ has been outlined in detail previously in our 2SLS analyses. Because the strategy is built to work in any GMM framework, we implement it here as well. For the LASSO stage, we allow the sets of selected Z and doubly selected X variables to vary flexibly across products. We then use the first stage prediction for each product $Z^m = \hat{1}_{\{m_{jbdt}>0\}} = Z_{jbdt}\hat{\theta}^Z_{jbt}$ as our instrument for $1_{\{m_{jbdt}>0\}}$.

In our preferred implementation, we jointly estimate the above (linearized) demand

[28] This is also closely related to the intuition behind Sinkinson and Starc (2017), who use managed care penetration to proxy for restricted choice sets in the statin market in any earlier time period.

model with the supply model using a generalized method of moments approach. This enables us to simultaneously recover the demand parameters θ, bargaining parameters, and marginal costs. It also imposes the constraints of the supply model that $mc_{jbt} \in [0, p_{jbt}]$, and $\frac{\partial s_{jbt}}{\partial p_{jbt}} \frac{p_{jbt}-mc_j}{s_{jbt}} \in [-1, 0]$ (though these constraints do not bind in our preferred model when demand is estimated separately).

4.3 Parameter Estimation Results

Table 8 shows the parameter estimates for the full model described above in Column (4), and for several intermediate models that help to illustrate how our instrumental variables move coefficient estimates in ways that are consistent with correcting the expected biases of estimation without instruments.

Table 8: Demand Parameter Estimates

	(1)	(2)	(3)	(4)
θ^m	0.10***	0.10***	0.10***	0.31***
	(0.01)	(0.01)	(0.01)	(0.10)
θ^p	0.0007***	-0.0037***	-0.0045***	-0.0040***
	(0.0002)	(0.0004)	(0.0005)	(0.0006)
λ^{ss}	0.78***	0.61***	0.59***	0.59***
	(0.00)	(0.01)	(0.01)	(0.01)
λ^{ms}	0.90***	0.13***	0.13***	0.14***
	(0.00)	(0.03)	(0.03)	(0.03)
$\overline{\eta_p}$	0.05	-0.16	-0.18	-0.16
$sd(\eta_p)$	0.06	0.21	0.24	0.21
$\overline{\eta_m}$	0.43	0.15	0.14	0.43
$sd(\eta_m)$	0.26	0.05	0.05	0.13
$sd(\theta_j)$	0.12	0.57	0.56	0.56
$sd(f(X))$	0.27	0.26	0.26	0.28
$sd(\xi)$	0.46	0.56	0.56	0.56
IV for:	–	$\ln(s_{\|g})$	$\ln(s_{\|g}), p$	$\ln(s_{\|g}), p, 1_{\{m>0\}}$

Estimates for nested logit demand $\ln(s_{jbdt}/s_{0dt}) = \lambda^{g_j} \ln(s_{jb|_g dt}) + \theta^m 1_{\{m_{jbdt}>0\}} - \theta^p p_{jbdt} + \theta_j + \theta_t + f_j(X_{jbdt}) + \xi_{jbdt}$ with separate nests for strong and moderate statins, 2011-12. $N = 124,216$ doctor-drug-brand-year observations with standard errors clustered at the doctor level ($N_d = 15,074$).

Column (1) estimates the model with no excluded instruments. The nesting parameters are large while the parameters on price and meals are very small in magnitude. The price coefficient is positive, which we might expect if changes in prices with the introduction of generic atorvastatin are larger for products whose residual demand is more affected.

Column (2) adds our instruments $\{Z^a, Z^p, Z^J, Z^m\}$ discussed above, and removes the within-group share terms $\ln(s_{|_g})$ from the instrument set (effectively replacing them with their predictions from the instruments, conditional on all other controls). Both nesting parameters decrease, consistent with the identification strategy correcting for the mechanical correlation of these terms with the unobservable. The coefficient on the moderate statins nest

decreases dramatically, which also seems consistent with the institutional details – strong statins are more highly differentiated from other forms of cholesterol management, especially for the very high cholesterol population.

Column (3) removes price p from the instrument set, which increases the magnitude of the price coefficient and elasticity by approximately 20 percent. Column (4) also excludes the meal indicator $1_{\{m>0\}}$ to now instrument for all of our endogenous variables, and the coefficient on meals triples, similar to what we observed in the single drug-year regressions of quantities on meals.

While the utility function parameters are difficult to interpret directly in terms of usage impact, the relative size of the meal and price coefficients suggest that a meal has an equivalent impact to a \$78 decrease ($= \theta^m/\theta^p$) in out-of-pocket price. While this seems like a large effect, it is partially driven by the lack of price sensitivity in statin consumption, which may in turn be driven by imperfect agency on the part of physicians and in part by cost-sharing subsidies for a large fraction of (LIS) enrollees. Perhaps more enlightening is the implied semi-elasticity $\eta_m = \frac{\partial s}{\partial m}\frac{1}{s}$, which measures the percent change in market share of the focal drug associated with a meal. The average of 43 percent suggests this payment effect is indeed substantial. However, the meal coefficient magnitude of 0.31 is not extreme in comparison to the variation vertically across product means ($sd(\theta_j) = 0.56$), or across physician observable ($sd(f(X)) = 0.28$) or unobservable ($sd(\xi) = 0.56$) dimensions.

Table 9: Product-Specific Demand and Supply Parameter Estimates

	Atorvastatin	Lipitor	Lovastatin	Pravastatin	Crestor	Simvastatin
θ_j	-2.56	-2.56	-4.03	-3.36	-2.71	-2.43
$\overline{\eta_p}$	-.08	-.51	-.03	-.02	-.34	-.02
$sd(\eta_p)$	.02	.31	.00	.00	.09	.00
$\overline{\eta_m}$	.45	.52	.36	.34	.54	.30
$sd(\eta_m)$	.07	.12	.01	.02	.08	.02
mc	0	0	0	0	0	0
B_{2011}	-	.62	.07	.07	.78	.05
B_{2012}	.18	.92	.05	.05	.99	.04

Product and year specific demand and supply parameters, 2011-12. $N = 124,051$ doctor-drug-brand-year observations with standard errors clustered at the doctor level ($N_d = 15,039$). All parameters different from zero at 1% level. Table with standard errors in Appendix.

Table 9 further breaks down the product-specific variation on the demand side, and also summarizes supply side parameters.[29] On the demand side, the most prominent pattern is the extent to which Lipitor/atorvastatin and Crestor are close substitutes on both the vertical (product means of -2.56 and -2.71) and horizontal ($\lambda^{ss} = 0.59$) dimensions. In contrast, the

[29]In the current implementation, we set marginal costs to zero. In the future, we will consider alternative proxies for marginal cost (e.g., the wholesale cost of the cheapest generic), as well as functional form restrictions on marginal cost that will allow us to separately recover marginal costs and bargaining parameters.

moderate statins are more heterogeneous both vertically and horizontally. This is reflected in the price and meal elasticities. Aside from their much higher prices, the closeness of the strong statins in product space provides strong unilateral incentives to provide meals to steal business from one another.xxv

This closeness of Lipitor and Crestor in product space does introduce a bit of a puzzle for why they are able to maintain such high prices relative to the generics. The model rationalizes this by assigning much higher bargaining parameters to these branded alternatives. Note that because the generic sales are aggregated over firms, the bargaining parameters are also providing proxies for within-molecule competitiveness.

These demand and supply estimates are interesting, but by themselves they cannot answer the policy question of the effect of payments on pharmaceutical markets. By construction, they measure the effect "holding all else equal", but both the focal firm and other firms in the market have meals and other strategic variables that may adjust to any policy change. And with the oligopoly structure of the market, these strategic reactions will depend on one another in equilibrium.

4.4 Assessing the Welfare Effects of Industry Payments to Physicians

To better understand the effects of payments to physicians on market welfare, we consider three counterfactual scenarios, all banning meals/payments from pharmaceutical firms to physicians. The first scenario bans payments, but fixes prices at those observed in the data. The goal here is to isolate the direct effect of payments on the market. The second scenario bans payments and allows prices to adjust to a new equilibrium, allowing for the fact that payments may affect prices as well as quantities. The third and final scenario bans payments and fixes out-of-pocket prices for all statins to marginal cost – an efficient static allocation benchmark. In each scenario, we compute equilibrium quantities and prices (except where prices are fixed as just mentioned), use these to calculate producer surplus, and then compute consumer surplus implied by the utility model of demand. We also compute the transfers from insurers to manufacturers/distributors implied by the new equilibrium quantities and point of sale prices. Table 10 displays various components of welfare under the observed data and counterfactual regimes. Each is shown in 2011 and 2012 separately in order to show how the results depend on market structure.

Focusing first on quantities, the primary result is that while payments do increase prescribing, on average they do so in a way that offsets the underprovision of statins due to market power keeping prices above marginal cost. Whether quantity with payments under-

Table 10: Welfare and Counterfactual Estimates

	2011				2012			
	(1) Obs	(2) $m=0$ p^{Obs}_{oop} p^{Obs}_{pos}	(3) $m=0$ p^{*}_{oop} p^{*}_{pos}	(4) $m=0$ p^{mc}_{oop} p^{*}_{pos}	(1) Obs	(2) $m=0$ p^{Obs}_{oop} p^{Obs}_{pos}	(3) $m=0$ p^{*}_{oop} p^{*}_{pos}	(4) $m=0$ p^{mc}_{oop} p^{*}_{pos}
$Q_{statins}$ (millions)	6.04	5.83	5.83	6.26	6.38	6.25	6.25	6.65
$Q_{atorvastatin}$	1.38	1.36	1.35	1.59	2.01	2.15	2.15	2.38
$Q_{Crestor}$	.97	.75	.76	.91	.98	.70	.71	.86
$\bar{p}_{statins}$ (\$, OOP)	19	18	18	0	16	15	14	0
$\bar{p}_{atorvastatin}$	39	39	40	0	24	23	23	0
$\bar{p}_{Crestor}$	42	42	42	0	38	38	37	0
PS_{retail} (\$ millions)	113.6	103.8	104.2	0	99.2	90.8	90.1	0
PS_{meals}	-0.5	0	0	0	-0.9	0	0	0
$PS_{transfers}$	218.1	196.4	196.9	352.8	184.8	153.4	151.6	301
PS	331.2	300.2	301.1	352.8	283	244.3	241.8	301
$PS_{atorvastatin}$	156.9	154.1	155.6	185.7	96.5	102.2	101.9	149.5
$PS_{Crestor}$	131.7	103.2	102.6	122.9	156.5	111.9	109.9	120.7
CS_{retail} (\$ millions)	1414.4	1359.9	1359.5	1471.8	1500	1465.3	1466.2	1573.6
CS_{meals}	-65.4	0	0	0	-44.9	0	0	0
$CS_{transfers}$	-218.1	-196.4	-196.9	-352.8	-184.7	-153.4	-151.6	-301
CS	1130.9	1163.6	1162.6	1119.1	1270.4	1311.9	1314.6	1272.6
TS (\$ millions)	1462.1	1463.8	1463.7	1471.8	1553.3	1556.1	1556.4	1573.6

or over-shoots the efficient allocation varies between Lipitor and Crestor. The model estimates that Lipitor is under-utilized in 2011 on the order of 1.35 million prescriptions with payments banned vs. 1.59 million at the efficient allocation, and the observed payments raise Lipitor to 1.38 million, only closing about 10 percent of the gap.

By contrast, the model predicts smaller shortfalls for Crestor of 0.76M in the no payments vs. 0.91M in the efficient scenario. Combined with the fact that Crestor provides many payments, this results in Crestor quantity under the observed payments of 0.97M exceeding the efficient benchmark allocation.

Looking at atorvastatin quantities after generic introduction in 2012 shows the importance of modeling strategic interaction and substitution across drugs. In 2012 Pfizer has almost completely stopped providing meals, and both Lipitor and generic atorvastatin are utilized less with meals than without because meals are driving substitution to Crestor.

These quantity effects highlight several of the issues motivated by the theory in Section 4.1 and Inderst and Ottaviani (2012). The extent to which payments distort efficient allocation depends upon their scale relative to that of the distortion due to market power maintaining high prices. In the market studied here, payments move closer to the efficient allocation. However, translating these quantity effects into surplus measures requires further analysis. It depends on the extent to which meals affect prices and/or better align consumption with

the true quality/cost tradeoffs of the various drugs in the market and vs. the outside option.

The new equilibrium prices in scenario (3) indicate that meals are having little effect on prices. The reason is that the combination of low price sensitivity of demand and negotiated prices that are often below firm profit maximizing levels mean that the price decreases we might expect with a meal ban are not made in this market.

Regarding the efficient allocation of consumers to specific products, the direct effect of payments is to move quantity towards the paying firm's drug in cases where it otherwise would not have been used. This results in a loss of consumer surplus of $\sum_{jb \in \mathcal{J}_t} q_{jbdt} \frac{\theta^m}{\theta^p} 1_{\{m_{jbdt}>0\}}$, which is calculated as CS_{meals} in the Table. This can be offset to the extent that payments steer patients towards better treatments – in particular, since two firms have patented drugs in 2011, payments may better align their market shares with their qualities – but the calculations of $CS_{retail} + CS_{meals}$ show this is not the case here. Banning payments results in an increase of \$10.9M (0.8 percent) in consumer surplus via allocation. These distortions are even stronger in 2012 when payments on net steer patients to Crestor in amounts that exceed the efficient allocation.

Even if consumer surplus is harmed, total surplus need not be. To the extent the market expands to allocate more statins to patients who should receive them at marginal cost, this will increase producer surplus in an efficient manner. However, because this is an oligopoly, some payments result in inefficient business stealing, which can harm consumer surplus (in this case does, per the allocation analysis in the prior paragraph) with no offsetting producer surplus gain. Here we see that this business stealing effect is sufficiently large that consumer surplus losses outweigh producer gains, resulting in payments being inefficient in terms of total surplus, in spite of moving closer to the aggregate efficient allocation on the extensive margin. Banning payments results in a slight increase of \$1.7M (0.1 percent) in total surplus in the retail market for statins.

While the above effects in the retail market all hint towards a value in banning payments, they leave out at least two important features of these payments. The first is the valuable information they may provide, which has been assumed to be zero due to the late stage of the statin market, but could be large in other contexts.

The second is their effect on the point of sale price p_{pos} that insurers pay, which is split among pharmaceutical manufacturers, distributors, and pharmacies. This number is difficult to compare with the others as it is a cost shared by all insured (not just those taking statins at a point in time), and so it is not easily translatable into a per person effect on premiums. With that caveat, however, the calculations under $CS_{transfers}, PS_{transfers}$ suggest that these drug cost effects are even larger in magnitude than the retail effects. Because payments steer patients toward more expensive drugs, they increase spending on statins by \$21.7M

(9.9 percent) in 2011 and $31.4M (20.5 percent) in 2012 relative to our counterfactual where payments are banned.

5 Conclusion

In many industries, firms reach consumers through expert intermediaries. Interactions between firms and these experts, which can involve direct payments and other kinds of remuneration, risk creating conflicts of interest that can hinder efficiency. However, these interactions can also facilitate valuable information flows, enhancing welfare. While recent theoretical work (Inderst and Ottaviani 2012) has shed new light on these tradeoffs, it has remained challenging to identify these relationships empirically. Specifically, it has been difficult to identify the causal impact of payments to experts on the advice they provide to end consumers. Payments are not random and likely correlated with characteristics of the expert. This gap in the literature is particularly important, given recent debates over conflicts of interest and disclosure in the US health care and financial services industries.

We address this gap by proposing a theoretical model which indicates a potentially useful instrumental variable to overcome the challenges of empirically estimating these effects in the health care industry. Using measures of the potential volume of patients for physicians and their local colleagues, we introduce plausibly exogenous variation in which physicians receive payments from pharmaceutical companies. We also exploit variation to market structure over time using the Lipitor patent expiration and ensuing generic entry. Leveraging this approach with detailed data on prescriptions, prices, and payments, we are able identify the impact of these interactions on prescribing behavior and overall welfare.

Overall, we generally find the IV estimates for the effect of meals on prescribing to be larger than OLS estimates for both 2011 and 2012. These results are consistent with firms targeting payments to physicians who would otherwise have prescribed the focal drug with low probability.

Despite these substantial effects on prescribing of the drugs that receive payments, our counterfactual welfare analysis of banning payments indicates that such a ban would have only a small, though positive, effect on consumer and total surplus. This is because high prices due to market power keep statin consumption – overall and of the powerful branded molecules – inefficiently low, and increased consumption due to payments partially offsets this, bringing the market closer to the efficient allocation, but at the cost of higher prices. We estimate the net effect of these two forces on consumers to be small but in favor of a ban. The overall increase in producer surplus is not large enough to offset this due to the fact that some of the increase is business stealing between the branded “strong statins" as

well as from cheap generic alternatives.

There are limitations in our approach. We focus on a narrow market, cardiologists and statin prescriptions, during a two-year time period near the expiration of the Lipitor patent. The dynamics of this market could differ in important ways from the statin market in an earlier phase, other drug and device markets in health care, and other industries where expert intermediaries play an important role, such as financial services. Future research can address these limitations, perhaps by building on our identification strategy for payments, which is quite general, or by providing alternative approaches to identify causal effects and model market responses.

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A Appendix: Payment Data Construction

A.1 Building the Dataset

The payment data is based on publicly available data released by firms prior to the Sunshine Act-required reporting that began in 2013. When posting these reports, each firm adopted its own standards for specificity,[30] categorization approach,[31] and accuracy. Physician-level identifiers were ambiguous and often limited to a name, city of address and perhaps a specialty. Furthermore, many of these documents have since been removed from easily accessible websites. During the period that these payments were still posted on the firms' websites, the enterprise software company Kyruus[32] collected these reports as a part of their initiative to analyze physician-firm interactions. In order to create a disambiguated physician-level dataset using the unstandardized reports, Kyruus utilized their proprietary machine-learning algorithms to match each individual-firm data point with the physician most likely to be the true recipient. The resulting dataset, generously provided to us by Kyruus, connects each firm-physician-payment to the most probable unique National Provider Identifier – a variable enabling us to merge this data to a number of other datasets.

There is significant heterogeneity in the nature of payments as they relate to the potential for conflict of interest. For example, a physician may receive a royalty payment for an invention sold by a company or a consulting payment for advice on product development. Other payments might not be related to a product at all. We construct two main categories of payments: "research" and "general" (all non-research payments). This scheme closely follows that of Open Payments and excludes all royalty payments. Within general payments we identify three sub-categories: "meals," "travel or lodging," and "consulting, speaking or education." Table 11 summarizes interactions levels for all of the firms, active physicians[33] and years of data we observe. In the focal analysis, we utilize only payments from Pfizer (who owns Lipitor) and AstraZeneca (who owns Crestor) to active Cardiologists.

The concern for misreporting, and in particular underreporting, in the early years of these documents led us to remove certain firm-year outliers.[34] To identify those firm-years most likely to suffer from significant misreporting, we collapsed each firm's annual total number of payments and payment amounts and dropped any firm-year for which either of these

[30] For example, while many firms reported whole dollar amounts, Allergan reported payments in large bins uninformative for analyses (e.g. \$1-\$1,000, \$1,001-\$10,000, etc.)

[31] Some firms utilized three mutually exclusive categories (e.g., consulting, meals, research), while others utilized non-exclusive labels (e.g., meals; meals, consulting; consulting, teaching and education).

[32] See: www.kyruus.com.

[33] Active prescribers here defined as being above the bottom 10th percentile of total annual claims in the Medicare Part D data.

[34] For anecdotes related to the inaccuracies of these early reports see: https://goo.gl/jDyHyS.

variables were an order of magnitude smaller than the most recent year's data. Given the relative stability in payment behaviors across firms and over time, we assume these sharp discontinuities were the the result of misreporting and not any dramatic change in firm policies.

Table 11: Firm-wide Total Interaction Amounts

Firm	Years	Avg. total, $M		Avg. total, n	
		General	Research	General	Research
AstraZeneca	2011-2013	$31.8	$0.95	115,490	119
Cephalon	2010-2013	$6.43	$10.5	27,736	258
EMD-Serono	2011-2013	$1.81	N.R.	7,070	N.R.
Forest	2012-2013	$39.8	$7.66	222,308	422
GlaxoSmithKline	2012-2013	$9.26	N.R.	40,989	N.R.
Eli Lilly	2011-2013	$35.8	$148	85,403	3,079
Merck	2012-2013	$22.3	$174	19,038	4,256
Novartis	2012-2013	$49.9	$74.4	99,129	2,853
Pfizer	2010-2012	$39.1	$93.9	137,012	1,855
Valeant	2010-2013	$1.78	N.R.	19,549	N.R.

Note: Expenditures and number of payments per year, dollars in millions. General and research payments are defined in text. N.R. indicates type was not reported ever.

B Relation Between Models

$$\ln\left(\frac{s_{jbdt}}{s_{0dt}}\right) = \lambda \ln\left(\frac{s_{jbdt}}{(1-s_{0dt})}\right) + \theta_{jd} + \theta^m 1_{\{m_{jdt}>0\}} - \theta^p p_{jbt} + \theta_t + \xi_{jbdt} \quad (10)$$

$$\ln\left(\frac{q_{jbdt}}{q_{0dt}}\right) = \lambda \ln\left(\frac{q_{jbdt}}{(Q_{dt}-q_{0dt})}\right) + \theta_{jd} + \theta^m 1_{\{m_{jdt}>0\}} - \theta^p p_{jbt} + \theta_t + \xi_{jbdt} \quad (11)$$

$$(1-\lambda)\ln\left(q_{jbdt}\right) = \lambda \ln\left(Q_{dt}\right) + (1-\lambda)\ln(q_{0dt}) + \theta_{jd} + \theta^m 1_{\{m_{jdt}>0\}} - \theta^p p_{jbt} + \theta_t + \xi_{jbdt} \quad (12)$$

$$\ln\left(q_{jbdt}\right) = \frac{\lambda}{1-\lambda}\ln\left(Q_{dt}\right) + \theta_{jd} + \theta^m 1_{\{m_{jdt}>0\}} - \theta^p p_{jbt} + \theta_t + \underbrace{\ln(q_{0dt}) + \xi_{jbdt}} \quad (13)$$

So the difference between the log claims and the nested logit is that the nested logit includes $\ln(q_{0dt})$ to make sure we are measuring the "residual" demand curve for each product. Thus where the reduced form will go wrong is not accounting for variables that drive demand for competing products that are also correlated with the focal product (e.g. prices and/or meals).