Physician-Industry Interactions: Persuasion and Welfare

(Under Revision – Please Do Not Cite Without Permission)

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

March 12, 2020

Abstract

In markets where consumers seek expert advice regarding purchases, firms seek to influence experts, raising concerns about biased advice. We combine a model of supply and demand with a local instrumental variables strategy based on regional spillovers from academic medical center conflict-of-interest policies to estimate the distribution of marginal treatment effects of pharmaceutical firm payments on physician prescribing, accounting for frictions like market power, negotiated prices, and insured demand. We find substantial heterogeneity across physicians in expected response to payments. Firms target payments to physicians with: a larger expected response, larger patient panels, and lower than average prescribing of the focal drug. Counterfactual estimates of the equilibrium response to a payment ban suggest that payments improve allocation by offsetting the distortion of high prices for on-patent drugs. We explore sensitivity of welfare estimates from our model, varying to the extent to which payments and the interactions that accompany them improve vs. distort prescribing. Total surplus typically increases with payments, but most of the gain accrues to manufacturers. Consumers only gain from payments if they mostly improve prescribing.

*University of Pennsylvania, The Wharton School & NBER, grennan@wharton.upenn.edu

†Harvard Business School, k.roy.myers@gmail.com

‡Columbia Business School & NBER, ats2180@gsb.columbia.edu

§Duke University, The Fuqua School & NBER, ronnie@duke.edu

The data used in this paper were generously provided, in part, by Kyruus, Inc. We gratefully acknowledge financial support from the Wharton Dean's Research Fund, Mack Institute, and Public Policy Initiative. Gi Heung Kim and Donato Onorato provided excellent research assistance. Abby Alpert, Alexandre Belloni, Colleen Carey, Pierre Dubois, Gautam Gowrisankaran, Robin Lee, and Amanda Starc, as well as numerous seminar and conference audiences, provided helpful discussion and feedback. Any errors are our own.

1 Introduction

Consumers often seek expert advice before making a purchase decision. This has long been the case in markets where decisions are complex or have large stakes, and where service from an expert intermediary is typically bundled with purchase, such as health care, finance, automobiles, housing, and luxury retail. In these contexts, experts can increase market efficiency by providing valuable information to consumers about product availability and quality. However, experts may also have objectives that diverge from those of consumers, raising concerns that their advice may be biased. In particular, experts frequently receive various forms of remuneration from firms selling in the market on which they offer advice, and there is a rich body of empirical evidence that experts respond to financial incentives.[1] Whether and how these expert-firm interactions impact welfare are contentious and important policy questions, animating debates over recent initiatives in the United States to address conflicts of interest, including the Department of Labor's Fiduciary Rule (2016), and in the health care context we study, the Physician Payment Sunshine Act (2010).[2]

In this paper, we consider the effects of payments from pharmaceutical firms to physicians who, in the US, frequently receive payments and other in-kind compensation, such as meals, from manufacturers of products they prescribe, inject, or recommend.[3] In general, both policy-making and empirical research regarding physician-firm interactions are complicated endeavors. A large literature has established that there is wide variation in both the remuneration and practice styles of health care providers in the US (see, e.g., Cooper et al. 2019; Finkelstein et al. 2016). This presents both an empirical difficulty and an object of interest to economic researchers. In particular, we expect that the observed and unobserved factors that make a given physician an attractive promotional target for a pharmaceutical firm will affect not only her prescribing *levels* – generating the usual concerns about endogeneity – but also the *slope* of her prescribing with respect to promotions.[4] The econometric issue is thus one of "essential heterogeneity" in that treated physicians may be selected to

[1] In the health care context, this phenomenon is known as "physician-induced demand" (McGuire 2000).

[2] For commentary, see, e.g., Rosenbaum (2015); Steinbrook et al. (2015), or the May 2017 issue of the *Journal of the American Medical Association*, which was entirely devoted to this topic.

[3] As noted in Scott Morton and Kyle (2012), promotion of pharmaceuticals embodies both potential inducements to use firms' products and some scientific information. In our study, we focus on payments from manufacturers to physicians, which is just one component of firms' promotional strategies. Millenson (2003) presents an overview of these practices for drugs and medical devices.

[4] The benefits and costs of targeting payments to a particular physician depend on the suitability of her patient population for the promoted drug, her knowledge and beliefs regarding treatment options (Agha and Molitor 2018; Cutler et al. 2019), and her susceptibility to promotion (i.e., her willingness to induce demand). Intrinsic factors that limit demand inducement may include psychic costs or professional ethics (McGuire and Pauly 1991); extrinsic factors may include the negative effects of inducement on patient flows or reputation costs (Dranove 1988; Pauly 1980; Rochaix 1989).

have relatively high treatment effects (Heckman et al. 2006); the economic issue is that the effects of any counterfactual policy on utilization and welfare will depend crucially on how the policy changes the mix of physicians receiving payments.

We study payments to cardiologists from pharmaceutical firms marketing statins, an important class of drugs that reduce cholesterol and the likelihood of heart attack and stroke. We combine data on payments, physician prescribing patterns, and numerous physician, hospital, and market characteristics to obtain a detailed picture of the the factors influencing both payments and prescribing. We use these data to estimate the distribution of the impact of payments on prescribing behavior. To obtain causal estimates, we leverage quasi-random variation in payments induced by the combination of variation in academic medical center conflict-of-interest policies, economies of scale in pharmaceutical sales activities, and physicians' geographic locations. We embed these estimates in a structural model of demand, pricing, and payment decisions that allows for several important features of the setting: market power, negotiated prices, insurance, and agency. We illustrate the economic tradeoffs inherent to payments in the face of other market imperfections by comparing the status quo to a counterfactual payment ban, a policy which is of interest in its own right, having been enacted by many medical centers and several states already.

For our empirical analyses, we link data on physician-firm-year-level payments 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. We focus on meals, which are the single most popular in-kind payment from pharmaceutical firms to physicians. Meals are also particularly relevant for our counterfactual analyses, having been subject to statutory bans in several states and health systems.[5] We further focus our examination on the market for statins in 2011-2012, as it is one of a few important markets with complete payment data prior to the introduction of OpenPayments.CMS.gov and it is also an extremely important class of drugs, one of the largest by both volume and revenue.[6] During this period, there were two branded statins (Pfizer's Lipitor and AstraZeneca's Crestor) and several generic substitute statins. Despite having prices around 10 times those of generic alternatives, these two branded drugs made up nearly 40 percent of the statins prescribed in our sample in 2011, and the majority of cardiologists received a meal from one or both of the manufacturing firms. The welfare effects of this are unclear, however, as Lipitor and Crestor were the first "strong

[5]Massachusetts, Minnesota, and Vermont had certain statutory gift bans during 2011-2012. As described in Larkin et al. (2017), nineteen academic medical centers nationwide introduced limits or bans on pharmaceutical representatives providing meals, branded items, and educational gifts between October 2006 and May 2011.

[6]The transparency introduced by OpenPayments.CMS.gov may alter the nature of physician-industry interactions; we consider this an interesting area for future research.

statins" shown to generate larger reductions in cholesterol, making them more appropriate for some patients.[7] Thus, while these drugs were expensive (as on-patent drugs typically are), they were also effective. Even if payments increase usage, this increase could be due to payments facilitating better information to physicians, or to payments counteracting a reduction in usage driven by high branded drug prices.

As noted above, the targeting of physicians to receive meals is not a random or innocuous process. Pharmaceutical firms invest heavily in sophisticated data and analytics, sales material development, and personnel training in order to get the word out to high-value physicians regarding their drugs' potential benefits. From our perspective as researchers, we expect the allocation of meals across physicians to be in part a function of the regional allocation of pharmaceutical sales representative "boots on the ground" to high-value markets based on disease prevalence, medical care organizational and market structure, geographic density of prescribers, and local factors that potentially limit inducement.[8] We also expect targeting decisions to be based on observed and unobserved physician-specific factors such as baseline prescribing tendencies and potential responsiveness to meals. These features of the environment argue in favor of a model of meal provision and prescribing behavior that allows for heterogeneity in treatment effects *and* endogenous targeting of meals as a function of a physician-specific treatment effect.

To trace out the distribution of treatment effects, we employ an identification strategy that exploits regional variation in Academic Medical Centers' (AMCs) Conflict of Interest (CoI) policies, which were designed to curb interactions between physicians and industry (e.g., banning on-site interactions). Using detailed data on these policies from the American Medical Students Association (AMSA) CoI Report Card scores, we document significantly lower rates of sponsored meals in regions with strict AMC CoI policies, even among physicians who are unaffiliated with the AMC and thus not directly subject to their policies. We argue that this result is consistent with economies of scale in firms' marketing efforts. Our empirical analysis assumes that, conditional on rich controls, AMC policies are unrelated to the latent preferences of *unaffiliated* physicians in the same region, motivating our use of these policies as instrumental variables.

Discussions with industry participants, supported by our data, indicate that payments between a firm and physician are highly persistent, particularly in mature markets such as the statin market we study. Given this, analysis of within-physician variation in meals over

[7]Strong statins are recommended for high-risk patients without any conditions that prohibit their use, so long as they tolerate the additional side effects that can accompany high-intensity formulations (Consumer-Reports 2014).

[8]In a notable recent example, Alpert et al. (2019) document that Purdue Pharma avoided marketing OxyContin in states with strict prescription drug monitoring programs.

time is likely to underestimate the treatment effect relevant for examining the welfare impact of these payments. Our identification strategy is thus cross-sectional in nature, focusing on which physicians do or do not receive payments. In order to support our exclusion restriction assumption – that regional AMC policies only affect the prescribing of unaffiliated physicians through their impact on drug firm payments to physicians – we include a rich set of physician- and market-level controls related to prescribing. The size of the potential control set we assemble, and the fact that we allow these variables to enter the model nonlinearly and interacted with other variables, creates a dimensionality and sparsity problem, which we address by drawing on the recent literature at the intersection of machine learning and econometrics. We follow a procedure outlined in Belloni et al. (2017), using LASSO regressions to select controls and an "orthogonalized" two-stage least squares (2SLS) regression to estimate the treatment effect of interest in a way that is robust to small errors in the variable selection process.[9]

To estimate the effects of physician payments in a market with many competing substitutes, two of which are promoted by competing firms, we estimate a discrete choice random utility model of demand for statins as a function of drug quality, payments, and patients' out-of-pocket prices. In addition to the instruments based on AMC CoI policies, we leverage the expiry of Lipitor's patent at the end of 2011, and ensuing generic entry, as an exogenous shock to both the choice set physicians faced and to out-of-pocket prices.

We find that meals lead to large increases in prescribing of promoted drugs. To put our estimate in context, it is equivalent to an increase in promoted drugs' cardiovascular prescribing market share from 4.12 percent, the sample average, to about 5.73 percent. This increase is close to half of a standard deviation in the observed prescribing heterogeneity across physicians. Our estimates also indicate that a meal has an equivalent impact to a $77 change in out of pocket price. We present estimates of the distribution of marginal treatment effects, which are consistent with pharmaceutical sales representatives successfully targeting meals to physicians with higher-than-average treatment effects. For example, while we estimate that the average treated physician increased promoted drug revenue by nearly $4,000 due to firm interactions, the same measure is only $1,300 among untreated physicians.

We also estimate a model of price negotiation between upstream manufacturers/distributors and insurers to capture the forces driving the point-of-sale prices that insurers pay for pharmaceuticals. Our results are sensible in that the estimated bargaining parameters are consistent with branded manufacturers receiving a large portion of the surplus they create, while

[9]LASSO stands for "least absolute shrinkage and selection operator." It is a commonly-used form of penalized regression that shrinks the least squares regression coefficients in a high-dimensional linear model towards zero (Varian 2014).

competition among many manufacturers drives down margins on generics dramatically.

The estimated demand and supply models allow us to consider the equilibrium response of prices and quantities to a ban on meals, and map those outcomes into welfare. We also analyze a counterfactual efficient benchmark scenario, where meals are banned and out-of-pocket prices are set at marginal cost. These exercises draw on the logic in Inderst and Ottaviani (2012), in which hidden kickbacks allow firms to expand market share without lowering prices, and welfare implications depend on the primitives and strategic interaction.[10]

In the market studied here, payments cause the market to overshoot the efficient level of branded statin usage. Our baseline estimates, with consumer welfare measured by our revealed preference demand estimates and meals assumed to be purely persuasive, indicates payments lower consumer welfare by $24M (1.6 percent) in 2011, relative to a counterfactual equilibrium with payments banned. These consumer losses outweigh producer gains, so that payments decrease total surplus as well. However, we concede that the additional patients receiving statins due to meals could have been clinically appropriate (perhaps because agency or other biases cause physicians to under-prescribe).[11] To explore this issue, we consider counterfactuals in which meal effects were partially informative. Our simulations suggest that consumer welfare suffers if 40 percent or more of meal effects are driven by physician-induced demand.

1.1 Related literature

This study fits into several literatures in industrial organization and healthcare economics. First, it contributes to a vast literature on potential conflicts of interest among expert intermediaries, across a diverse set of markets. In health care contexts, financial incentives have been shown to impact physicians' prescribing behavior, quantity of services provided, referral patterns, and procedure recommendations (Afendulis and Kessler 2007; Clemens and Gottlieb 2014; Gruber and Owings 1996; Ho and Pakes 2014; Iizuka 2012; Chen et al. 2016). Outside the health care context, conflicted experts have been found to provide suboptimal, or in extreme cases fraudulent, life insurance recommendations (Anagol et al. 2017), financial advice (Egan et al. 2018), auto repair diagnoses (Schneider 2012), and mortgage loan recommendations (Robles-Garcia 2020). A notable subset of this literature highlights the agency problem between experts and consumers by studying market equilibria when ex-

[10] 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. However, as noted in Inderst and Ottaviani (2012), disclosure may have limited real-world effects. E.g., Pham-Kanter et al. (2012) find that early state-based physician payment disclosure laws had a negligible to small effect on physicians switching from branded therapies to generics and no effect on reducing prescription costs.

[11] See summary in Baicker et al. (2015).

perts are themselves consumers. See, e.g., Johnson and Rehavi (2016) regarding physicians as patients, and Levitt and Syverson (2008) regarding real estate agents selling their own houses. Of these, Robles-Garcia (2020) is perhaps closest to ours, in that it uses estimates of supply and demand to simulate the net welfare impact of eliminating expert inducements in an imperfectly competitive market. In her study, UK mortgage brokers are incentivized to recommend high-commission, expensive products; however, banning broker commissions reduces welfare by increasing households' shopping costs and reducing the competition faced by large lenders. Our studies provide complementary evidence on how a general economic phenomenon can have nuanced and potentially differing welfare effects across different institutional settings.

This paper also contributes to the literature on payments and physician decision-making. A number of studies have examined the correlations between payments and prescribing, including Datta and Dave (2016); DeJong et al. (2016); Mizik and Jacobson (2004); Yeh et al. (2016).[12] In recent work, both Agha and Zeltzer (2019) and Carey et al. (2020) have used specifications with physician fixed effects to estimate the incremental effects of payments on prescribing. These papers have a somewhat different focus than the current study: Agha and Zeltzer (2019) quantify how the targeting of "key opinion leader" physicians impacts anticoagulant prescribing among non-targeted physicians; Carey et al. (2020) estimate the immediate effects of incremental payments on the quality and quantity of prescribing in a wide range of drug classes. Because meal payments are typically combined with interactions between sales representatives and physicians, payments also relate to a literature in marketing on pharmaceutical sales representative detailing visits to physician offices (Chintagunta and Manchanda 2004; Guo et al. 2019; Manchanda and Honka 2009; Narayanan and Manchanda 2009). We contribute to this literature using an identification strategy that is designed to estimate the treatment effect of interest for evaluating the welfare effects of a full ban on payments. To that end, we also perform a particularly detailed case study to recover the supply and demand estimates necessary for welfare simulations in a complex environment.

Finally, our work builds on the findings of several recent studies of marketing in oligopoly settings: e.g., Dubois et al. (2018) examine the effects of a ban on junk food advertising; and Alpert et al. (2015), Shapiro (2018), and Sinkinson and Starc (2018), estimate causal effects of direct-to-consumer advertising (DTCA) on drug utilization. For example, Dubois et al. (2018) use supply and demand estimates to illustrate how both equilibrium prices and quantities adjust when a ban is imposed. We contribute to this literature in that we study targeted promotional activity which is unobserved by end-consumers, rather than public and undifferentiated advertising. We document meaningful heterogeneity in treatment effects,

[12] Kremer et al. (2008) provides a review of early research on this topic.

consistent with strategic targeting behavior by firms. We estimate larger effects of detailing than previously documented for DTCA in drug markets, which may be driven by the hidden nature of detailing, the fact that it is directed to expert physicians rather than inexpert patients, or both.

2 Setting, Data, and Empirical Strategy

2.1 Setting: Drugs, Doctors, Firms, and Patients

We focus on cardiologists prescriptions of statins 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. (2) 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. (3) These statins were each the chief source of revenue from cardiologists' prescribing for these two firms, with Lipitor accounting for 84 percent of Pfizer's cardiologist-driven revenues and Crestor similarly accounting for 80 percent 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.[13] (4) Lipitor's patent expiration offers a large and visible shock to statin prices and substitutes, helping to identify demand curves.[14]

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. Statins are generally considered to be effective drugs with few side effects. The American College of Cardiology (ACC)'s 2013 guidelines recommended statin therapy for adults with elevated risk of atherosclerotic cardiovascular disease; full adoption under these guidelines would have increased statin use by 24 percent (American College of Cardiology 2017). Statins are close substitutes for most patients, but atorvastatin (Lipitor) and rosuvastatin (Crestor)

[13]Cardiologists as a specialty account for 10 percent of Part D statin claims. Even though cardiologists write relatively few prescriptions, they are targeted because specialist prescriptions are sustained by primary care physicians (Fugh-Berman and Ahari 2007).

[14]The generic version of Lipitor (atorvastatin) became available in December 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 percent, from $2.5 billion (13 million claims) in 2011 to $591 million (2.8 million claims) in 2012.

are available as high-intensity statins appropriate for some patients with elevated risk.[15]

The structure of Medicare Part D (see Appendix A.1 for detail on the program)implies that enrollees should be sensitive to price variation across and within branded and generic drugs.[16] This sensitivity may be muted by various frictions, including enrollees' limited understanding of coverage and physicians' imperfect agency.[17] Part D plan issuers' strategies and profits are heavily regulated by the Centers for Medicare and Medicaid Services (CMS), but they have both motive and opportunity to constrain costs through formulary design (drugs' placement on tiers), negotiations with drug manufacturers, and negotiations with pharmacies.[18]

2.2 Physician-Firm Interactions

Firms' promotional strategies generally include direct-to-consumer advertising, "detailing" to physicians, advertisements in venues targeted to physicians, and various forms of payments made directly (or in-kind) to physicians. These "payments" from firms to physicians most often surrounds the provision of meals. We focus exclusively on these meals because they account for more than 95% of the physician-firm interactions we observe.[19] During these meals, sales representatives target prescribers with product presentations regarding safety, efficacy, side effects, convenience, compliance, and reimbursement. These in-the-field sales representatives are considered "the most expensive and, by consensus, highest-impact promotional weapon" in pharmaceutical firms' arsenals (Campbell 2008). Because it is very likely that these meal-centric relationships are persistent over long periods of time and there is not a large amount of variation in the dollar amount of meals when outliers are excluded, we focus primarily on understanding the effect of having a meal-based relationship with a firm, proxied by whether we ever observe the cardiologist to receive a meal from a firm in the few years of data we observe.[20]

[15] 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).

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

[17] E.g., enrollees are more responsive to current prices than marginal prices, and respond disproportionately to salient coverage changes such as copay changes for entire drug classes (Abaluck et al. 2018).

[18] E.g., Duggan and Scott 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.

[19] On a dollar basis, in our sample, meals account for roughly 16% of all direct payments to physicians. But this is almost entirely driven by less than 1% of physicians receiving very large payments due to consulting, speaking, and travel fees.

[20] For 90% of our sample, the total dollar value of meals received in a year (conditional on receiving any) is less than $200. We can observe Pfizer meals for 2010–2012 and AstraZeneca meals for 2011–2013.

2.3 Data Sources

2.3.1 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.[21] 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.[22]

Prescribing behavior is based on the publicly-available CMS Part D claims data for 2011 and 2012.[23] These claims data describe total prescription claims and spending for each prescriber-drug-year. The prescriber information includes physicians' National Provider Identifier (NPI), which allows us to link claims data to the Physician Compare database as well as industry interaction data. Drugs are defined by brand and molecule name (if the drug is "generic," these two are equivalent). Claims may vary in terms of unobserved drug dosages, days supplied, and formulation. However, we are unaware of any evidence that industry payments target particular dosages or presentations, so we follow prior studies in analyzing claims directly (Einav et al. 2015).

Our price variables are the plan enrollment-weighted average point-of-sale and unsubsidized out-of-pocket prices per one-month supply for each Part D pricing region-drug-year from the Medicare Part D Public Use Files. One month is the modal supply per 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 hierarchy of drug categories that 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 two measures of prescribing outcomes: (1) log quantity of the focal drug's claims; and (2) (for the structural analysis) the focal drug's share of all cardiovascular (ATC code = "C") and statin (ATC code = "10AAC") prescribing within physician-year.

[21] See: https://data.medicare.gov/data/physician-compare.

[22] See: https://www.dartmouthatlas.org for more. HRRs represent regional health care markets for tertiary medical care. Each HRR has at least one city where both major cardiovascular surgical procedures and neurosurgery are performed. HSAs are local health care markets for hospital care. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area. There are 3,436 HSAs and 306 HRRs in the US.

[23] See: https://www.cms.gov/Research-Statistics-Data-and-Systems/Research-Statistics-Data-and-Systems.html.

2.3.2 Data on firm payments to providers

Although federally mandated reporting of manufacturer-provider payments did not begin until 2013, nationwide interest had been growing for some time. By 2010, states had begun to institute their own payment limitations and/or public reporting rules;[24] a number of high-profile lawsuits found conflicts of interest between physicians and manufacturers to be a punishable offense;[25] and calls from politicians and patient advocacy groups were gaining momentum (Grassley 2009). Amidst this growing concern, a number of firms, including Pfizer and AstraZeneca, began to publicly release data on payments to physicians, often due to legal settlements.[26] These documents are the basis of our payments data, which were generously shared by Kyruus, Inc.[27]

2.4 Data Set Construction and Summary Statistics

Starting with the full sample of cardiologists in the Medicare Physician Compare database, as identified by their self-reported primary specialty, we restrict our sample to "active" Medicare prescribers with at least 500 Part D claims on average in 2011 and 2012; this is approximately the 10^{th} percentile of claims per physician-year. We then restrict the sample to cardiologist-statin molecule pairs that have at least two non-zero observations (which is required to estimate the mean utility parameter). The final sample used in our analyses contains about 13,000 cardiologists. In terms of focal drugs, we focus on the six most popular statins (two branded, four generic) available during 2011–2012.[28]

Table 1 summarizes the claim quantities, drug prices, and meal-based interactions for our sample. The effect of entry by generic atorvastatin in December 2011 is clear – in its first full year of availability, this new alternative accounted for roughly 22 percent of cardiologists' statin claims, while Lipitor's share dropped from 22 percent in 2011 to about 5 percent in

[24]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.

[25]For example, in 2009 Eli Lilly paid a $1.4 billion fine following allegations of the off-label promotion of its drug Zyprexa (United States Department of Justice 2009).

[26]The existence of some voluntary disclosures is not entirely surprising. 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. For more, see: https://projects.propublica.org/d4d-archive/.

[27]The raw disclosures were published 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 by Kyruus to create a disambiguated physician-level dataset of payments from Pfizer and AstraZeneca in 2011 and 2012. Appendix B.2 compares this data to that made publicly available post-Sunshine Act and finds no evidence of any major biases or censoring in our data.

[28]These account for more than 99 percent of Part D statin claims and expenditures in this period.

2012.

The middle columns of Table 1 summarize prices. As expected, branded Lipitor and Crestor both had high out-of-pocket (OOP) and point-of-sale (POS) prices in 2011, relative to generics. In 2012, generic atorvastatin entered with intermediate OOP and POS prices due to limited generic competition in its first year. While other generic drugs' prices were somewhat lower in 2012 than in 2011, both Pfizer and AstraZeneca increased their POS prices in 2012. Finally, while Crestor's OOP price was the same in 2011 and 2012, Lipitor's OOP price increased dramatically, as insurers removed Lipitor from their formularies (Appendix A.2 provides further detail on 2012 pricing).

The rightmost columns of Table 1 describes the proportion and magnitudes of the meal-based interactions from the branded manufacturers. AstraZeneca was clearly more aggressive at this time, which was most likely connected to the eventual entry of generic atorvastatin, an (approximately) perfect substitute for Lipitor.

Table 1: Summary Statistics

	Claim Count, avg.		Out-of-Pocket Price, avg.		Point-of-Sale Price, avg.		In-sample Meals		
	2011	2012	2011	2012	2011	2012	>0, frac.	$\frac{\$}{\text{year}}$, avg.	$\frac{\$}{\text{year}}$, $p90$
All Drugs	3,289.5	3,416.6							
All Cardio.	2,516.6	2,618.8							
All Statins	385.2	411.6							
Crestor	61.4	63.4	45.71	42.97	137.04	160.30	0.73	58.83	138.00
Lipitor	87.9	21.5	42.29	91.48	120.12	142.97	0.38	18.70	59.00
Atorvastatin		108.4		11.10		31.88			
Other Generic (3)	235.8	218.2	5.20	4.20	13.51	10.45			

Note: Based on 127,011 cardiologist-molecule-brand-year observations during 2011-2012.

2.4.1 Potential Observable Covariates

Because our strategy for estimating physicians' responsiveness to meals will be based on cross-sectional variation, it is important that we can account for the many different factors that generate across-physician variation in their utilization of statins, and likelihood of being targeted with meals by these firms. Table 2 below outlines the set of covariates we will use. To summarize, we include sets of variables that capture the number of patients a physician treats with certain types of drugs, variables that describe a wide range of characteristics related to the sizes and types of own and adjacent organizations, and variables regarding the insurance and health status of local populations. Together, these form the set of potential control variables to be included in our meal regressions.

Table 2: Overview of Observable Covariates

Cardiologist	Hospital	ZIP code
Num. Practice Zip Codes[1]	Num. Cardio. & Doc. Affiliated[1]	Spot TV Ad Units[4]
Num. Hospital Affiliations[1]	Num. AAMC Affils.[2]	Spot TV Ad Spend[4]
Num. Practice Affiliations[1]	Num. AAMC Faculty[2]	Spot TV Ad Duration[4]
Num. Specialties[1]	Share Doc. AAMC Faculty[2]	
Is AAMC Faculty[2]	Hospital Beds & Admissions[3]	
Is Female[1]		
Years since Med. School[1]		
HSA & HRR	**State**	
Num. Cardio. & Doc. Affiliated[1]	Medicare Part D / Advantage Enrollment[1]	
Num. AAMC Affils.[2]	Low-income-subsidy Enrollment in Medicare Part D / Advantage[1]	
Num. AAMC Faculty[2]		
Share Doc. AAMC Faculty[2]		
Teaching Hosp. Bed & Adms. Share[3]		
Medicare Advantage, N Eligible & %Covered[4]		
Pop., %Uninsured & %Medicaid[5]		
Cardiac Hospitalization Rate[5]		

Notes: Aggregations of each variable are averaged at the cardiologist. In each level of aggregation, the subsumed level associated with the focal cardiologist is excluded in a jackknife procedure. Superscripts indicate data source. [1]CMS Part D Public Use Files & CMS Physician Compare Data; applicable to all claims data. [2]American Academic Medical Center Faculty Roster. [3]American Hospital Association Annual Survey. [4] Nielsen Ad Intel. [5]CMS Medicare Advantage enrollment and landscape files. [6]Behavioral Risk Factor Surveillance Survey.

In total, we amass 75 covariates that describe many of the differences across physicians, hospitals, and markets that are likely to be related to the way physicians choose drugs, and firms choose which physicians to interact with. This includes physicians' demographics, hospital patient volumes, local TV advertising, and regional health and socio-economic indicators. Still, we have no special a priori knowledge as to which of these covariates (or transformations thereof) are most relevant. But our research design will be partly based on our ability to accurately predict the use of drugs, and targeting of meals. This motivates our use of Lasso-based variable selection protocols described below.[29]

2.5 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, directly or via their marketing contractors, typically first determine marketing budgets and strategies based on aggregate market characteristics. 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, and pharmaceutical sales forces maintain rich databases on prescribers' practice characteristics, prescribing behavior,

[29]See the appendix for a table of summary statistics of a selected subset of these variables.

and history of interactions with the firm (Campbell 2008). They then target physicians based on the expected incremental costs and benefits of sales effort. The expected benefit of interacting with a given physician depends on the size and appropriateness of the physician's patient panel, the physician's latent preferences over substitute products, and the physician's expected responsiveness to inducement. Costs include the labor costs of additional sales representatives, the opportunity costs of diverting sales effort from other physicians, and any direct costs of the interaction (e.g., meal expenditure); they also implicitly include factors that limit or prohibit access for sales representatives. 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, pressures on physicians that limit available time for firm interaction, etc. (Khedkar and Sturgis 2015).

Pharmaceutical sales territories are defined by geography and other organizing principles, such as therapeutic area (Campbell 2008). 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 – variables that proxy for attractiveness of *other* physicians in the same geographic market are useful instruments for interactions.

The variables we focus on for identification are academic medical centers' (AMCs') conflict of interest policies. These are described in detail in Larkin et al. (2017). We rely on data on AMCs' conflict of interest policies from the American Medical Student Association's (AMSA) conflict of interest scorecard. The AMSA scores evaluate the strictness of AMC policies regarding physician interactions with pharmaceutical/device companies, including salesperson access to AMC facilities, gifts to physicians, and enforcement of the policies.[30] We hypothesize that regions where AMCs have strong conflict-of-interest policies, as captured by high AMSA scores, will see less meal payments to physicians overall, even to those

[30]In every school year since 2007, medical schools have been asked to submit their policies to the AMSA for rating. Each institution's policy is graded in 13 different categories, including Gifts, Consulting, Speaking, Disclosure, Samples, Purchasing, Sales Reps, On-Campus, Off-Campus, Industry Support, Curriculum, Oversight, and sanctions for Non-Compliance. For each category except Oversight and Non-Compliance, the institution is assigned a numerical value ranging from zero to three. A zero is awarded if the institution did not respond to requests for policies or declined to participate; a one if no policy exists or the policy is unlikely to have an effect; two if the policy represents "good progress" towards a model policy; and a three if the policy is a "model policy." We generate aggregate AMSA scores for each institution; this aggregate ranges from 11 to 31-32 in 2011-2012.

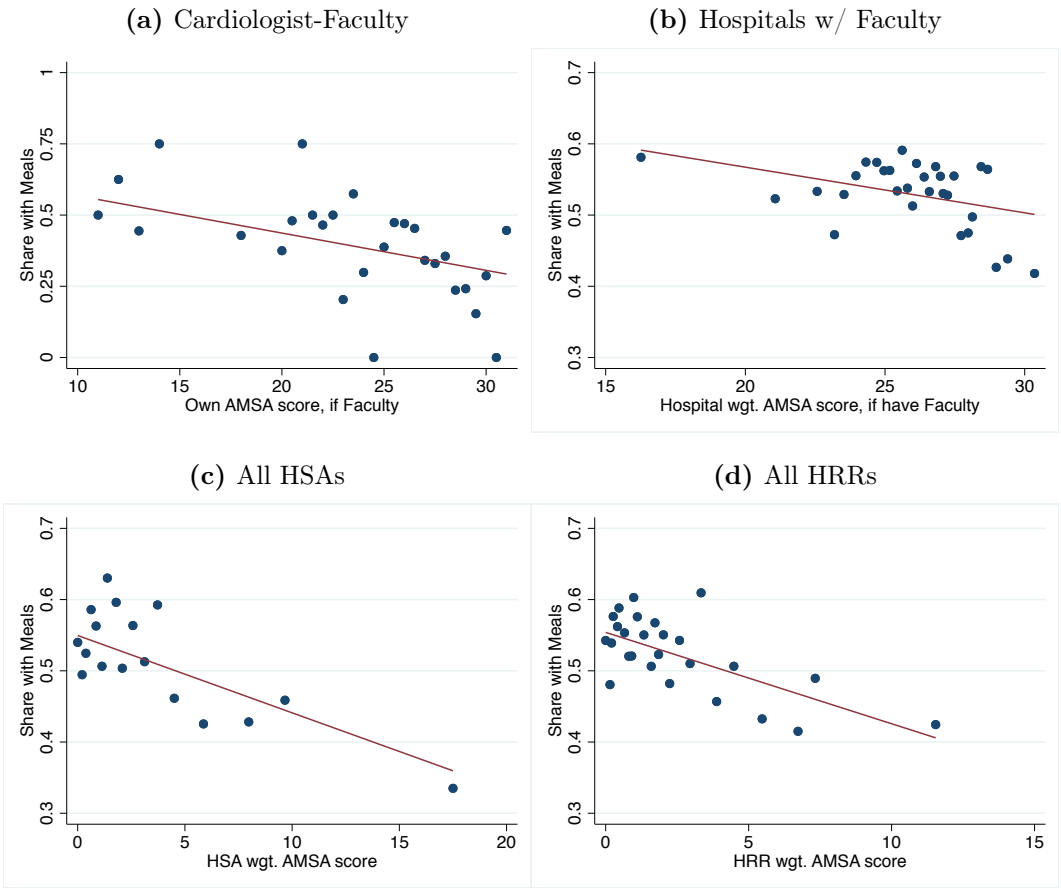
physicians unaffiliated with the AMCs. We further hypothesize that these effects will be stronger when a larger portion of the region's cardiologists are affiliated with the AMC and for cardiologists located more closely to the AMC in geographical space.

To get a sense of our approach, consider Sioux Falls, SD and Lubbock, TX, two cities whose major HRRs surround moderately-sized state universities with associated AMCs: the University of South Dakota and Texas Tech University, respectively. These markets each have 24-28 cardiologists in our sample. However, the USD AMSA CoI score is 30, vs. only 24 at Texas Tech, and many more of the cardiologists in the Sioux Falls region are faculty than in the Lubbock region. These differences are associated with large differences in meal rates: 16 percent in the Sioux Falls region vs. 41 percent in the Lubbock region. Simultaneously, we see large differences in prescribing of branded statins: 2.1 percent of cardiovascular drug prescriptions by Sioux Falls-area cardiologists are for branded statins, vs. 2.9 percent for Lubbock-area cardiologists. Of course, there may be other important differences in Sioux Falls vs. Lubbock that we want to account for, including the illness of the patient population, insurance rates, managed care penetration, and so on, which motivates our control inclusion and selection procedure described below.

Moving to the aggregate numbers, the top two panels in Figure 1 show the raw relationships between meal receipt and AMSA CoI scores for: individual cardiologists affiliated with AMCs (panel a), hospitals with affiliates who are also AMC faculty (panel b), hospital service areas (panel c), and hospital referral regions (panel d). The faculty linkage is from the Association of American Medical Colleges (AAMC) faculty roster. Each analysis is performed at the cardiologist level, and each AMSA variable excludes the lower units of aggregation associated with the same focal cardiologist:"Hospital" AMSA scores exclude the scores of the focal cardiologist; "HSA" (hospital service area) scores exclude the scores associated with cardiologists at the focal cardiologist's hospital; and "HRR" (hospital referral region) scores exclude the scores associated with cardiologists in the focal cardiologist's HSA.

While we might expect conflict of interest policies to have large effects on pharmaceutical company interactions with the cardiologists and hospitals under their jurisdictions, that does not necessarily make them valid instruments. The exclusion restriction may fail due to direct effects of conflict of interest policies on norms regarding prescribing, or due to unobservable factors correlated with selection into more restrictive policies. We address this concern by leveraging identification from jackknifed versions of AMSA scores at the HSA and HRR levels. These raw relationships are shown in the bottom two panels in Figure 1. Exposure to stricter local AMC conflict of interest policies still has a significant negative effect on meals, even though those policies do not directly govern the focal cardiologist's own or affiliated hospital's behavior.

Figure 1: Raw AMSA Score – Meal Correlations



Notes: Each panel plots unconditional meal probabilities (averaged over all firm-years) per AMSA CoI policy scores (larger scores indicate more "stringent" policies that dissuade industry relationships). Weighted score metrics ("wgt.") are averages over regions where the value of the AMSA variable for faculty cardiologists is the score of their affiliated school, and for non-faculty cardiologists the value equals 0.

This first stage relationship is assumed to be driven by marketing economies of scale that result in local spillovers at the HSA and HRR levels. In the results section, we use the model estimates to provide evidence consistent with this assumption. This exclusion restriction assumption is consistent with conversations with current and former pharmaceutical sales executives and pharmaceutical marketing consultants. Under this assumption, instruments based on jackknifed HSA and HRR AMSA variables are exogenous with respect to the focal cardiologist's own preferences over drugs and susceptibility to inducement, conditional on a rich set of controls for cardiologist and market characteristics. We cannot test this directly, but we examine placebo checks on this assumption in Section 5.

2.5.1 A note on "meals" and cross-sectional identification

Our identification strategy has two nuances that deserve further discussion. First, our estimates of the effects of "meals" on prescribing behavior may be proxying for the effects of a long-term sales relationship between a physician-firm pair. Second, our cross-sectional instrumental variables approach 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.

We consider our approach to be appropriate for several reasons. First, 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. (2020), Yeh et al. (2016), and DeJong et al. (2016)). Our conversations with pharmaceutical marketing specialists and consultants indicate that physician-firm relationships involve repeat interaction by design. This is confirmed in our data, in which payments are highly persistent across years: about 70 percent of cardiologists that received a meal from AstraZeneca in 2012 also did so in 2011.

This places our study in contrast to Carey et al. (2020), Datta and Dave (2016), Mizik and Jacobson (2004), in which the researchers include physician fixed effects to take out persistent unobserved differences across physicians.[31] The average treatment effect of a pharmaceutical firm providing one fewer meal to a physician in the context of a long physician-firm relationship, 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. Thus we argue that a cross-sectional identification strategy is most appropriate for considering a counterfactual ban on meals, our interest here. This emphasizes the importance of controlling for a rich and flexible function of physician, hospital, and regional variables, to account for heterogeneity in prescribing patterns.[32]

3 Model of Pricing, Payments, and Demand

In this Section, we present a model of supply and demand that allows us to analyze the net welfare effects of industry interactions with physicians. We hypothesize that such interactions increase prescribing of promoted drugs. This finding would have little to say about welfare on

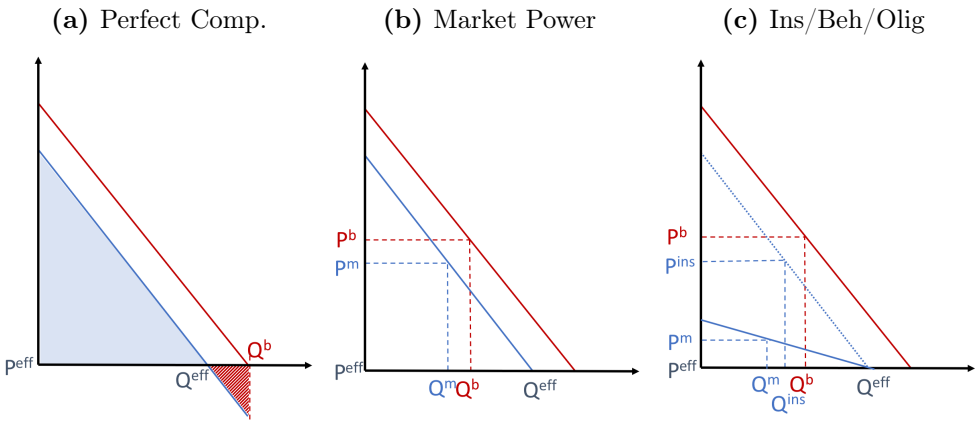
[31] Carey et al. (2020) contains an additional innovation: they address patient panel endogeneity using patients' moving behavior.

[32] A particular strategic decision of firms that may be correlated with meals are other advertising efforts (i.e. DTCA). But since these sorts of initiatives typically target broad geographic territories (i.e. via television markets), we believe that we can adequately account for any impact they may have with our regional level controls under the assumption that firm's advertising decisions are some function of these controls.

its own: in this context, welfare analysis of physician-firm interactions must account for market power, strategic interactions, insured demand, and the possibility that physician/patient decision making could be imperfect due to physician agency or physician/patient behavioral biases. For this, we develop an explicit demand model of how consumers trade off the influences of meals and prices and substitute across competing drugs. We also develop a supply model of how prices are determined in equilibrium for given demand and market structure.

To build intuition regarding this point, consider the welfare effects of interactions that shift the demand curve outward. Panel (a) of Figure 2 presents a hypothetical demand curve in blue and a "biased" demand curve shifted outward in red. Assuming without loss of generality that the drug's marginal cost is zero, the welfare loss under perfect competition is shown in the shaded triangle below the line segment $\overline{Q^{eff}Q^{b}}$ – marginal patients prescribed the drug in the presence of physician-firm interactions receive negative health benefits.

Figure 2: Welfare Analysis with Other Frictions



In a setting with perfect competition, this conceptual framework suggests that a simple analysis of the causal effects of payments on prescribing is all that is needed. However, in many empirically-relevant settings with firm payments to experts, firms also have market power, and utilization is distorted away from the social optimum due to high prices (Inderst and Ottaviani 2012). In prescription drug markets, branded products have patent protection, and they often compete with differentiated branded and generic substitutes whose manufacturers make their own strategic pricing and promotion decisions. A simple version of this model is presented in panel (b) of Figure 2: a branded pharmaceutical manufacturer faces the residual demand curve in blue, which is again shifted outward in the presence of physician-firm payments. Market power causes "unbiased" quantities Q^m to be too low; thus, payments may increase prescribing toward the optimum $Q^m < Q^b < Q^{eff}$ (pictured) or

cause prescribers to overshoot the optimum $Q^m < Q^{eff} < Q^b$. In the former case, the overall welfare impact of payments is positive, though consumer surplus declines; in the latter case, both total and consumer surplus decline. In our structural analyses, we model this supplier market power and incorporate it into our counterfactual analyses.

Finally, we must also account for reasons that the "effective" demand curve for a given drug may not represent the appropriate one for welfare analysis. A leading example is insurance, pictured in panel (c) of Figure 2. The "true" demand curve is the solid blue line; the insured residual demand curve is the dotted blue line (which is significantly less elastic with respect to the producer's price, as insurance enrollees bear only a fraction of that price out of pocket); and the "biased" demand curve is again in red. In this hypothetical, payments from firms reinforce the effects of insurance, each increasing consumption above the uninsured equilibrium: $Q^m < Q^{ins} < Q^b$. The welfare implications are again ambiguous, and the consumer surplus effects of firm payments will depend on pass-through of producer prices to enrollee premiums. In our structural analyses, we account for the details of patient insurance and model prices as determined via bilateral bargaining between insurance plans and pharmaceutical suppliers.

The general point of panel (c) extends beyond insurance. In oligopoly, the residual demand curve can be distorted due to competitor pricing or payment behavior. This is the phenomenon highlighted in Inderst and Ottaviani (2012), where payments may even increase consumer surplus by improving allocative efficiency. Further, a large literature in health care markets finds that utilization of health care products and services can be biased due to information frictions and imperfect agency. As documented in Baicker et al. (2015), such "behavioral" biases could be positive or negative.[33] While welfare analysis in the presence of behavioral frictions is notoriously problematic (Bernheim and Rangel 2009), we take advantage of the additional information available regarding pharmaceutical product effectiveness, and complement our revealed preference estimates with welfare estimates based on the clinical literature regarding the health benefits of statins.

3.1 Demand for Pharmaceuticals

In this Section, we describe a discrete choice random utility model as a model of demand for statins, taking physician-firm interactions (meals) and prices as given. Let the utility of molecule $j \in \mathcal{J} = \{0, 1, ..., J\}$, for use case i (a doctor/patient/visit combination) in each market – defined by doctor d in year t – be given by: $u_{ijdt} = \delta_{jdt} + \varepsilon_{ijdt}$.[34] The choice

[33] See Figure A5 for one hypothetical extension of panel (c) with a downward behavioral bias.

[34] The only molecule sold in both branded and generic format during the time period we study is Lipitor / atorvastatin in 2012. They have different j indices, allowing preferences for the two to be potentially

$j = 0$ represents the choice of treatment other than a statin, with mean utility normalized to $\delta_{0dt} = 0$. We measure the market size of potential statin patients as the number of all cardiovascular prescriptions, including other lipid-modifying drugs, for each physician-year. The use-specific i.i.d. unobservable $\varepsilon_{ijdt} = \epsilon_{idt} + (1-\lambda)\epsilon_{ijdt}$ is the random coefficients representation of the nested logit model (Cardell 1997), where ϵ_{idt} is a random component common to statins vs. alternative treatments, and ϵ_{ijdt} is the standard type I extreme value error term (with scale normalized to one) that is i.i.d. across molecules. As the nesting parameter $\lambda \in [0, 1]$ approaches 1, there is less substitution outside the nest. In this case, mean utility across use cases is specified as:

$$\delta_{jdt} = \theta^m_{jd} 1_{\{m_{jd}>0\}} - \theta^p p^{oop}_{jdt} + X_{jdt}\theta^x_j + \xi_{jdt} \ . \tag{1}$$

Here $\theta^m_{jd} 1_{\{m_{jd}>0\}}$ is an indicator for whether provider d received a meal from the manufacturer and its utility weight. Importantly, this utility weight may be specific to the drug-doctor pair. It may even be negative and lead to decreased prescribing. This heterogeneity across drugs and doctors in the impact of a meal on mean utility captures several sources of variation that have been discussed in prior research (e.g., Inderst and Ottaviani 2012) such as: the persuasive/informative nature of the interactions associated with meals, physician prior knowledge/ability, physician concern for patients, and the fraction of patients that are wary/sophisticated/informed. These underlying mechanisms are difficult to disentangle empirically, but doing so is unnecessary for our purposes. In our empirical exercises, we quantify the overall net effect of payments on prescribing, and the counterfactual effect of a payment ban.

Turning to the other components of mean utility, $\theta^p p^{oop}_{jdt}$ is the average out-of-pocket price paid by patients and its weight. $X_{jdt}\theta^x_j$ is a rich set of covariates that captures perceived quality variation across molecules, as well as regional and provider variation in prescribing patterns over time (we return to discuss this in detail when we discuss estimation of the model in Section 4). Finally, ξ_{jdt} is a product-physician-year unobservable preference heterogeneity term.[35]

Given a set of products available to a provider $\mathcal{J}_{dt}$ and flow of choice opportunities Q_{dt}, we assume the provider/patient chooses the product that maximizes utility, so that quantities

different and flexibly estimated.

[35]Several recent papers (e.g., Dubois et al. (2018); Shapiro (2018); Sinkinson and Starc (2018)) focused on television advertising have explicitly focused on the possibility that such ads can have spillover effects across brands in a category. Our identification strategy based on regional returns to scale is not ideal for this task, and so we omit these spillovers from our specification. We discuss this omission in our results.

demanded are given by:

$$q_{jdt} = Q_{dt} Pr[u_{ijdt} > u_{ikdt}, \forall k \in \mathcal{J}_{dt}] = Q_{dt} \frac{e^{\frac{\delta_{jdt}}{1-\lambda}}}{\sum_{k \in \mathcal{J}_{dt}} e^{\frac{\delta_{kdt}}{1-\lambda}}} \frac{\left(\sum_{k \in \mathcal{J}_{dt}} e^{\frac{\delta_{kdt}}{1-\lambda}}\right)^{1-\lambda}}{1 + \left(\sum_{k \in \mathcal{J}_{dt}} e^{\frac{\delta_{kdt}}{1-\lambda}}\right)^{1-\lambda}}, \tag{2}$$

and consumer surplus across all products is given by:

$$CS_{dt}(\mathcal{J}_t) = Q_{dt} \frac{1}{\theta^p} \ln \left(1 + \left(\sum_{j \in \mathcal{J}_{dt}} e^{\frac{\delta_{jdt}}{1-\lambda}}\right)^{1-\lambda}\right) - \underbrace{\alpha^{bias} \sum_{j \in \mathcal{J}_{dt}} q_{jdt} \left(\frac{\theta^m}{\theta^p} 1_{\{m_{jd}>0\}}\right)}_{\text{adjustment for meal "bias"}}, \tag{3}$$

which is the standard formula derived by McFadden (1978), minus an adjustment for the fact that a change in prescribing due to meals may affect prescribing but not patients' utility. The parameter $\alpha^{bias} \in [0, 1]$ determines the extent of this adjustment. $\alpha^{bias} = 1$ could be interpreted as a case where meals only bias providers away from otherwise optimal prescribing. $\alpha^{bias} = 0$ could be interpreted as a case where meals represent an exchange of information that only improves prescribing.[36]

3.2 Pricing Pharmaceuticals

We next characterize how prices are set in equilibrium. Let the supplier's profit be: $\pi(p^{pos}_{jrt}) = \sum_{d \in r} q_{jdt}(p^{pos}_{jrt} - mc_{jt})$, where mc_{jt} captures the cost of manufacturing and distributing the marginal unit of molecule j. p^{pos}_{jrt} is the point-of-sale price insurers pay for the drug, which we model as constant across providers within region r. We link the negotiated point-of-sale price and out-of-pocket price paid by enrollees via $p^{oop}_{jdt} = cs_{jdt} p^{pos}_{jrt}$, where cs_{jdt} is an exogenous cost-sharing parameter that can vary across markets and years, depending on product mix and insurer mix (discussed in detail in Appendix A.2). In our main estimates, we take the region r over which point-of-sale prices are negotiated to be the state.

We assume that prices of substitute drugs in the market are determined in a simultaneous Nash Equilibrium of Nash Bargaining between suppliers (these include manufacturers, wholesalers, and pharmacies) and buyers (PBMs/insurers).[37] This captures the primary forces relevant to our research question, abstracting from some of the details of the up-

[36] A related (and not mutually exclusive) interpretation would be that physicians maximize a sum of physician (chooser) and patient (consumer) utility, and $\theta^m_{jd} 1_{\{m_{jd}>0\}}$ is only partially patient utility, with $\alpha^{bias} \in [0, 1]$ governing the extent.

[37] As discussed by Starc and Swanson (2019), both pharmacies and pharmaceutical manufacturers have market power, but relative market power of different suppliers varies by drug. Pharmacies make larger margins on generic drugs than on branded drugs, while branded manufacturers command higher markups (even net of rebates) than generic manufacturers.

stream interactions between suppliers, and from insurer competition and insurance plan structure.[38] 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. The first-order conditions of this model (see the Appendix for details) generate pricing equations that can be represented by:

$$p^{pos}_{jrt} = mc_j + b_{jrt}\left[\left(1+\sum_{d\in r}\frac{\partial q_{jdt}}{\partial p^{oop}_{jdt}}\frac{p^{oop}_{jdt}-mc_j}{\sum_{d\in r}q_{jdt}}\right)\frac{\sum_{d\in r}\widetilde{CS}_{dt}(\mathcal{J}_{dt})-\widetilde{CS}_{dt}(\mathcal{J}_{dt}\setminus j)}{\sum_{d\in r}q_{jdt}}+p^{pos}_{jrt}-mc_j\right] \quad (4)$$

Here the term $b_{jrt}\in[0,1]$ is a bargaining ability parameter, weighting the extent to which the optimal price depends on supplier profits ($b_{jrt}=1$) vs. the expected additional buyer surplus ($b_{jrt}=0$) in the case that a contract is agreed to for product j: $\widetilde{CS}_{dt}(\mathcal{J}_{dt})-\widetilde{CS}_{dt}(\mathcal{J}_{dt}\setminus j)$. Note that quantities and thus elasticities are driven by physician/enrollee 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}. We follow recent papers on insurer-hospital bargaining (e.g., Gowrisankaran et al. 2015; Ho and Lee 2017) by using a parameter $\alpha^{cs}\in[0,1]$ to capture the relative weight insurers place on consumer surplus, and subtracting plan costs: $\widetilde{CS}_{dt}(\mathcal{J}_{dt}) := \alpha^{cs}CS_{dt}(\mathcal{J}_{dt})-\sum_j q_{jdt}(p^{pos}_{jrt}-p^{oop}_{jdt})$.[39]

3.3 Modeling Meals

In this Section we provide a model of the decision by a given drug manufacturer to supply a meal to a given doctor. This model conditions on a global optimization of how to budget meals and the salesforce to execute them across geographic space. As neither our estimation strategy nor our counterfactuals will require solving that global problem, we do not consider it here. Given that global allocation, product j's sales representative should supply a meal to doctor d if the return on investment exceeds whatever hurdle rate R_j the firm applies, which is if and only if:

$$(p^{pos}_{jr}-mc_j)\left(E[q^{m_{jd}=1}_{jd}-q^{m_{jd}=0}_{jd}|\mathcal{I}_{jd}]\right) > R_j\left(C^{m_{jd}=1}_{jr}-C^{m_{jd}=0}_{jr}\right). \quad (5)$$

Here we assume that the negotiated point of sale price in a region will not change with a meal supplied to one more physician. The key terms are then what the sales representative

[38] These details are captured in a reduced form sense by the bargaining and cost-sharing parameters. Our counterfactual analysis will hold these fixed. This assumes that banning meals to physicians does not change the fundamental supply chain of the pharmaceutical industry or the general treatment of branded and generic therapies in insurance plan formularies.

[39] In contrast to these papers, we model pricing of a single product class (statins) rather than a bundle of products. Thus α^{cs} in our setting may also capture how plan enrollment might respond to disagreement in this particular product class. Olssen and Demirer (2019) documents substantial plan switching based on which statin brands are on formulary in Medicare Part D.

expects to happen to quantity, given her information set $\mathcal{I}_{jd}$, and the effect of the meal (both direct and indirect) on total costs in the region.

The institutional details in this setting suggest that the cost function $C_{jr}^{m_{jd}=1}$ will have increasing returns to scale in the sense that the average cost of providing a meal will be decreasing in the total meals provided in a region. We would also expect the cost function to depend on other regional characteristics such as the density of candidate physicians in geographic space. Further, the incremental cost of providing a meal to doctor d is likely to depend on characteristics of that doctor or her employer that affect her willingness to accept a meal.

The expected quantity increase from the meal $E[q_{jd}^{m_{jd}=1} - q_{jd}^{m_{jd}=0}|\mathcal{I}_{jd}]$ will be a function of the expectation of total size of the doctor's patient flow Q_{dt} and the choice probability function as given in (2). In particular, it will be a function of the expectation of the parameter θ_{jd}^{m} which determines the effect of the meal interaction on the mean utility the doctor assigns to product j. As discussed earlier, pharmaceutical manufacturers invest heavily in data and analytical tools to support sales representative decision making, and representatives also develop their own, more difficult to quantify, assessments of doctors through sources such as other doctors and staff. This suggests that representative meal decisions are likely to be based on data we have available as researchers, plus other factors that are unobservable to us. This induces the potential for selection on unobservables, both in levels and in terms of the response to the meal "treatment." The next Section maps the theory, data, and institutional details into an estimation strategy that addresses these challenges,

4 Identification and Estimation: Price Elasticities, Meal MTEs, and Bargaining Model Parameters

In this Section, we show how the demand and meal models described thus far can be fit into a standard potential outcomes framework, embedded in the structural demand system. The potential for selection both into treatment with a meal and on the (heterogeneous) response to treatment suggest a local instrumental variables strategy, using the data and institutional details discussed previously. We also need to identify and estimate the other parameters of the demand system, in particular the price and nest parameters, which face the common simultaneity/endogeneity problems inherent to demand estimation.

Our estimation approach proceeds in three broad steps. We outline the strategy here and fill in details in the remainder of the Section. In the first step, we estimate the price and nest parameters as well as a rich set of molecule-doctor fixed effects. For these we use

instrumental variables that leverage the variation over time in prices and choice sets induced by the introduction of generic atorvastatin. We then set up a potential outcomes framework where the molecule-doctor fixed effects are the outcome of interest and are functions of a host of features that affect persistent prescribing differences, in particular long term relationships embodied by which doctors do or do not receive meals, and meals are modeled in a first-stage selection equation. The second step is the estimation of this selection equation, which produces a propensity score for meal allocation across doctors as a function of regional, hospital, and doctor characteristics, including instrumental variables based on academic medical center conflict of interest policies and regional economies of scale in sales force allocation. The third step then uses this estimated selection equation in a local instrumental variables estimation to recover the distribution of marginal treatment effects across the sample of molecule-doctor observations.

As a preliminary step, we first linearize the demand model, following Berry (1994). We set choice probabilities implied by the demand model in Equation (2) equal to observed market shares, and invert the system of equations to obtain mean utilities as a function of the market shares: $\delta_{jdt} = \ln(s_{jdt}/s_{0dt}) - \lambda \ln(s_{j|_g dt})$. Combining this with Equation (1) yields the linear specification:

$$\ln(s_{jdt}/s_{0dt}) = \lambda \ln(s_{j|_g dt}) + \theta^m_{jd} 1_{\{m_{jd}>0\}} - \theta^p p^{oop}_{jdt} + X_{jdt}\theta^x_j + \xi_{jdt} \ . \tag{6}$$

where s_{jdt} is j's overall market share, s_{0dt} is the market share of the outside good (non-statin treatments), and $s_{j|_g dt}$ is j's market share within nest g, the set of statin treatments. The theory outlined thus far suggests that $\ln(s_{j|_g dt})$, p^{oop}_{jdt}, and $1_{\{m_{jd}>0\}}$ are all likely correlated with the unobservable term ξ_{jdt} as well as any unobservable component of the response to meals θ^m_{jd}.

4.1 Estimating price sensitivity and nest parameters

In the first stage of estimation, we implement a differences-in-differences style estimator to leverage the price and choice set variation resulting from the introduction of generic atorvastatin at the end of 2011. We find this to be the most compelling specification to identify the coefficients on price and within-nest share. We estimate:

$$\ln(s_{jdt}/s_{0dt}) = \lambda \ln(s_{j|_g dt}) - \theta^p p_{jdt} + \psi_{jd} + \theta_t + \theta_{Lip12} + \tilde{\xi}_{jdt} \tag{7}$$

where ψ_{jd} is a product-doctor-specific fixed effect and θ_t is a year-specific coefficient, providing a differences-in-differences interpretation of the remaining variation. We further include

θ_{Lip12}, a coefficient for Lipitor in 2012, to capture the fact that demand for branded Lipitor is small and idiosyncratic in 2012 as it is removed from formularies over the course of the year. With a slight abuse of notation, we use a single fixed effect for both branded Lipitor and generic atorvastatin in order to leverage the within-molecule variation in price between 2011 and 2012 induced by generic entry.

We leverage both the average changes induced by generic atorvastatin entry and also the heterogeneity in insurer responses to this entry across geography (described in detail in Appendix A.2). When Lipitor's patent expired, some insurers instantly added generic atorvastatin to their preferred drug lists and/or removed Lipitor from their formularies, while others took more than a year. The variation in penetration of these insurers across geography generated large variation in the relative prices consumers faced for Lipitor and generic atorvastatin. To utilize this variation, we create instruments for each plan-drug-year-region as the average out-of-pocket price for that drug-year-insurer across *other* regions. We then average across plans to create an instrument for physician d's region. We also create an analogous instrument based on an average dummy for formulary coverage, alone and interacted with the Lipitor dummy. The instrument set is then: $Z^p = [p_{jdt}^{oop,IV}, \bar{1}_{\{j \in form_{dt}^{IV}\}}, \bar{1}_{\{j \in form_{dt}^{IV}\}} \cdot 1_{\{j=Lipitor\}}]$. These are similar to the bargaining ability instruments in Grennan (2013, 2014) and Dickstein (2016), with the added benefit of a clear mechanism driving their variation. 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 generic statins prescribed $Z^J = [\ln(|\mathcal{J}_{dt}^{gs}|), |\mathcal{J}_{dt}^{gs}|, |\mathcal{J}_{dt}^{gs}|^2]$ as an instrument. This leverages the fact that more variety will mechanically affect within-group shares. In this particular context, it is also closely related to the intuition behind Sinkinson and Starc (2018), who use managed care penetration to proxy for restricted choice sets in the statin market in an earlier time period.

4.2 Estimating the effects of meals on prescribing

The fixed effects ψ_{jd} from the first step of our estimation capture all of the sources of persistent prescribing differences across doctors during our sample period. We now turn to recovering the determinants of this prescribing heterogeneity, in particular, the extent to which it is influenced by meals from pharmaceutical firms. To do this, we project the product-doctor fixed effects on our cross-sectional meal indicator and a rich set of controls

for physician and market characteristics.[40]

$$\hat{\psi}_{jd} = \theta^m_{jd} 1\{m_{jd} > 0\} + X_{jd}\theta^x_j + \bar{\xi}_{jd} \ . \tag{8}$$

In our preferred specification, we construct $1\{m_{jd} > 0\}$ as a dummy for physician d receiving any payment from Pfizer over 2010-2012 (in the case of j=Lipitor/atorvastatin), or as a dummy for physician d receiving any payment from AstraZeneca over 2011-2012 (in the case of j=Crestor).[41] We estimate this equation only on observations for Lipitor/atorvastatin and Crestor, as generic firms do not provide meals to doctors.

In order to accommodate the fact that meals are not randomly allocated to physicians, we also specify a selection equation that is a semi-parametric form of the meals model in Equation (5).[42] This selection equation takes the form of a linear probability model:

$$1\{m_{jd} > 0\} = Z_{jd}\gamma^z_j + X_{jd}\gamma^x_j + \mu_{jd} \ . \tag{9}$$

4.2.1 Selection propensity and MTE via local linear IV

The outcome equation (8) and selection equation (9) fit into the canonical potential outcomes framework. As discussed previously, there is likely selection into treatment with a meal payment on both levels and the response to treatment. In the context of the model, the unobservable in the selection equation μ_{jd} is correlated with both $\bar{\xi}_{jd}$ and the heterogeneous component of θ^m_{jd}. It has been well established that in such a case the standard 2SLS estimator will be biased upwards relative to the true LATE. We thus follow the literature and estimate the marginal treatment effects directly. We can then estimate many treatment effects of interest as a function of the distribution of MTEs.

We take a semi-parametric approach to MTE estimation. We first estimate the propensity to receive a meal using the linear probability model in (9). We then use the residuals from this estimated propensity score model (which the literature typically refers to as the "unobserved resistance to treatment") and use local linear instrumental variables regressions to map out the MTEs across observations with similar unobserved resistance to treatment.

[40] The idea of a secondary regression to uncover the determinants of fixed effects goes back at least to Mundlak (1978).

[41] Payments from AstraZeneca in 2010 are not available in our data.

[42] Appendix C.1 shows the tight relationship between the selection equation here and a structural version of the model in (5) for a particular cost function with increasing returns to scale.

4.2.2 LASSO Selection of Controls/Instruments

The cross-sectional nature of our identification strategy and the data-intensive nature of our semi-parametric MTE estimation strategy both make a rich set of controls and flexible functional forms especially important. Relatedly, we have no a priori theory for the functional form relating our potential instruments to meals. To address these issues, we include a large set of potential controls at the regional, hospital, and doctor level. We include linear, quadratic, and logarithm terms of each variable. We also include the potential instruments based on AMSA scores of local AMCS and their interactions with the relative presence of the AMC in the region and geographic location of each doctor. We also include linear, quadratic, and logarithm of these instruments, and further interact them with dummy variables for each manufacturer. As we allow the control and instrument sets to grow larger and more flexible, we run into the issues of sparsity and collinearity which have been the topic of a growing literature at the intersection of econometrics and machine learning. We follow Belloni et al. (2017) and related literature in using LASSO to select the controls and instruments which most strongly predict meals and prescribing. The appendix discusses the details of this procedure.

4.3 Supply Model Estimation

The demand model estimates provide the utility parameters needed to compute demand elasticities and consumer surplus in the equilibrium observed in the data. They can also be used to estimate market shares and consumer surplus under counterfactual scenarios where any given product j is removed from the choice set, but prices of the remaining products stay the same. These are the critical inputs needed for the bargaining model. The remaining parameters to be identified by the supply model are the marginal costs, the bargaining ability weights, and the insurer concern for consumer surplus vs. profits, α^{cs}.

In our preferred specification, we set marginal costs to zero, parameterize bargaining ability parameters as a function of product and regional fixed effects, and specify the econometric unobservable as the residual variation in bargaining parameters needed to fit the model to the data. We then estimate the insurer concern for consumer surplus and bargaining ability parameters via GMM, using consumer surplus measures calculated at average prices in other regions to avoid potential simultaneity bias.[43]

[43]The fact that consumer surplus is a function of price can create an endogeneity problem where the surplus measures are correlated with the unobservable in the supply pricing equation.

5 Determinants of Meals and the Effect of Meals on Prescribing Patterns

The demand and meal selection model estimates in Table 3 provide interesting insights into the drivers of meals and prescribing patterns. The first step estimates of price and nest parameters match basic institutional details and prior literature. The nesting parameter of 0.586 indicates that there is much more substitution within statins than to non-statin alternatives. This matches institutional knowledge that there are certain types of cardiovascular patients for whom statins are appropriate. The price coefficient is small, as we would expect given the muted incentives implied by insurance, and the related own-price elasticity $\eta_p = \frac{\partial s}{\partial p}\frac{p}{s}$ equals -0.101. This small elasticity is in a similar range as prior estimates for the Part D setting (e.g., Abaluck et al. 2018; Einav et al. 2018) and is consistent with insurer negotiating power preventing manufacturers from fully exercising their market power. The appendix provides more details on the distribution of product-doctor fixed effects and the Bayesian shrinkage procedure we use to account for noise in their estimation.

Table 3: Demand Estimates

	OLS	2SLS		OLS		2SLS		MTE
	(1)	(2)		(3)	(4)	(5)	(6)	(7)
θ^p	-0.00013***	-0.00309***	θ^m	0.0633***	0.0634***	0.545***	0.438***	0.238***
	(0.000034)	(0.000149)		(0.00524)	(0.00519)	(0.106)	(0.0978)	(0.011)
λ	0.974***	0.586***						
	(0.00125)	(0.0170)						
avg. ϵ^p	-0.101	-0.164	avg. ϵ^m	0.131	0.132	1.132	0.911	0.493
s.d. ϵ^p	0.121	0.190	s.d. ϵ^m	0.0120	0.0120	0.103	0.0830	0.351
N obs.	113,136	113,136	N obs.	23,553	23,553	23,553	23,553	23,553
F.E. set	$jd, t, t_{\text{Lipitor}}$	$jd, t, t_{\text{Lipitor}}$	X set	Regional	All	Regional	All	All
F stat.		708.8	F stat.			72.8	79.7	n/a

Notes: Columns (1–2) report the price (θ^p) and statin nest (λ) coefficient estimates and corresponding price elasticities. Columns (3–7) report the meal (θ^m) coefficient estimates and corresponding meal semi-elasticities. All of these models use our Lasso protocol for covariate and instrument selection (if 2SLS/MTE). For columns (1–6), standard errors are clustered at the doctor level. For column (7), θ^m corresponds to the LATE estimated using the MTE-based protocol, and the standard error is based on 500 doctor-level jackknife samples.

In the following columns, we show the results of several different specifications of equation (8). Columns (3)–(4) present the results estimated via OLS; these indicate that meal receipt is correlated with a 13 percent increase in promoted drug prescribing. Columns (5)-(6) display 2SLS estimates, which are significantly larger than the OLS, indicating the average physician receiving a meal will increase their utilization by 90-113 percent. Column (7) presents our preferred estimate of the local average treatment effect from the MTE protocol described in Section 4.2.1; the estimated meal LATE drops dramatically, indicating that

meals increase prescribing among compliers by 49 percent. This is larger than the OLS estimate and smaller than the 2SLS estimate, suggesting the presence of both "negative selection on levels" – sales representatives allocate meals to many physicians who otherwise would prescribe relatively low amounts of their drugs – and "positive selection on slope" – sales representatives target physicians with relatively high responsiveness to meals.[44] To put these results in context, the relative size of the meal and price coefficients suggest that a meal has an equivalent impact to an \$77 decrease ($= \theta^m/\theta^p$) in out-of-pocket price.

Our primary finding here – that the interactions surrounding meal payments from industry to physicians have a meaningful effect on physician prescribing (nearly four times that of the OLS correlation) – is large in relative magnitude, but not necessarily surprising in the context of popular press and industry insider writings on pharmaceutical sales.[45] It is different in nature and larger than estimates using within-physician variation, which intuitively estimate the effect of an additional meal for an individual physician who is likely involved in an ongoing relationship; in contrast, our instrumental variables strategy seeks to estimate the causal effect of the entire meal relationship vs. the counterfactual with no relationship. However, there are a number of modeling choices underlying our estimates, and cross-sectional causal identification is inherently difficult.

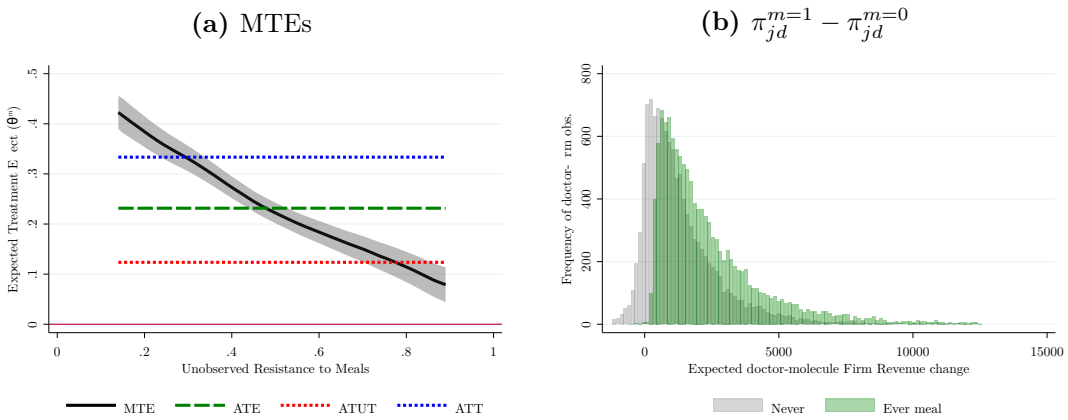
5.1 MTEs of Meals on Prescribing

To put the difference between the 2SLS and MTE results in context, consider the left panel of Figure 3, which shows the distribution of marginal treatment effects in physicians' unobserved resistance to treatment (with 95% confidence intervals), along with horizontal lines demarcating the population average treatment effect (ATE), the average treatment effect among treated physicians (ATT), and the average treatment effect among untreated physicians (ATUT). The steep downward slope in the MTE curve highlights the dramatic heterogeneity in meal responsiveness across physicians. The difference between the ATT and ATUT demonstrates that firms successfully targeted highly-responsive physicians to receive meals. Finally, the difference between the ATE and ATT highlights the importance of heterogeneity in thinking about appropriate counterfactuals; the relative effect of banning meals among treated physicians (selected endogenously by firms) is much larger than it would be

[44] Intuitively, if there are decreasing returns to persuasion across the claims distribution – marginal claims are harder to "buy" as volume increases, a result we obtain below that is consistent with physicians being constrained in the number of suitable patients they see – then it is efficient for firms to have a strategy that targets many smaller payments to (relatively) more responsive, but lower-volume, physicians.

[45] E.g., this is consistent with the observation in industry publications that physicians may be high-value either because they are already high prescribers, or because they are initially low prescribers but can be influenced by targeted marketing (Fugh-Berman and Ahari 2007).

Figure 3: Heterogenous Effects of Meals on Prescribing



from a baseline in which all physicians received meals.

To understand the profitability of this targeting behavior, the right panel of Figure 3 shows a histogram the incremental effect of meals on pharmaceutical firm revenues per physician, separately for treated and untreated physicians. As evidenced by the significant rightward shift in the distribution of incremental revenues for treated physicians (relative to untreated physicians), meals increased treated cardiologists' prescribing revenue to drug firms by nearly $4,000. However, counterfactually extending meals to all untreated cardiologists would have increased prescribing revenue to drug firms by only about $1,300.

5.1.1 Determinants of Meals and Prescribing

The second step – the meal selection equation – provides some insights into the correlates of meal provision and the first-stage impacts of our instrumental variables. Column (1) of Table 4 shows that physicians in regions with strict CoI policies (high AMSA scores) receive fewer meals. Column (2) shows that, consistent with the economies-of-scale argument, this relationship is stronger for regions where more cardiologists are (as faculty) subject to those CoI policies. Finally, column (3) shows that the spillover effect from AMCs' CoI policies to unaffiliated physicians is stronger when the physicians' practice locations are geographically close to the AMC.

Table 5 shows the variables with the most predictive power in explaining meals and prescribing, as well as the signs of their coefficients in a linear regression with standardized coefficients, so that parameter values can be interpreted as the impact of a one standard deviation change (for continuous variables) in either the probability of receiving a meal or mean utility.

Table 4: IV 1st Stage Effects and Economies of Scale Mechanism

	Hospital Referral Region (HRR)		
	(1)	(2)	(3)
AMSA level	-0.0550***	-0.0511***	-0.0586***
	(0.00980)	(0.00984)	(0.0101)
AMSA level ×		-0.0208***	
Faculty Share		(0.00777)	
AMSA level ×			0.0782***
Drive Time to AAMC			(0.0258)
N Obs.	24073	24073	24073

Notes: Reports coefficients from doctor-firm level meal propensity regressions using standardized transformations of the AMSA I.V.s. AMSA "level" is the mean AMSA score of AAMCs within the region (HRR; where HRR-based instruments jackknife AMSA scores of the focal doctor's HSA). "Faculty Share" and "Drive Time to AAMC" interact the AMSA level with the share of faculty members in the region or the time required to drive from the focal doctor's primary practice location to the nearest AAMC in their region, respectively.

5.1.2 Placebo Checks

In this study, we do not have a clear placebo in the form of an alternate or subsample to check for spurious effects. However, the fact that we have estimates of meal treatment propensities for each observation based on rich controls and instruments allows us to perform a test of certain types of spurious effects that would be present if our instrument failed the exclusion restriction. Specifically, we compute the meal propensity for each observation as a function of controls only, and we look at how the effect of our instruments in the reduced form regression varies with this estimated propensity score. We are particularly interested in the regions where $Pr(Meal|X) \approx 0$ and $Pr(Meal|X) \approx 1$. In these regions, observations are nearly guaranteed to either not receive a meal or receive a meal, no matter the value of the instruments – the first stage is essentially shut down, and thus meal receipt cannot explain variation in prescribing. If the exclusion restriction holds, the reduced form effect of our instruments in these regions should move toward zero. If, on the other hand, our exclusion restriction fails because say high AMSA regions also have doctors who are unobservably less likely to prescribe the branded strong statins, even conditional on controls, then we would expect the reduced form effect to remain positive even as the first stage is shut down as a mechanism. The results are shown in Figure 4.

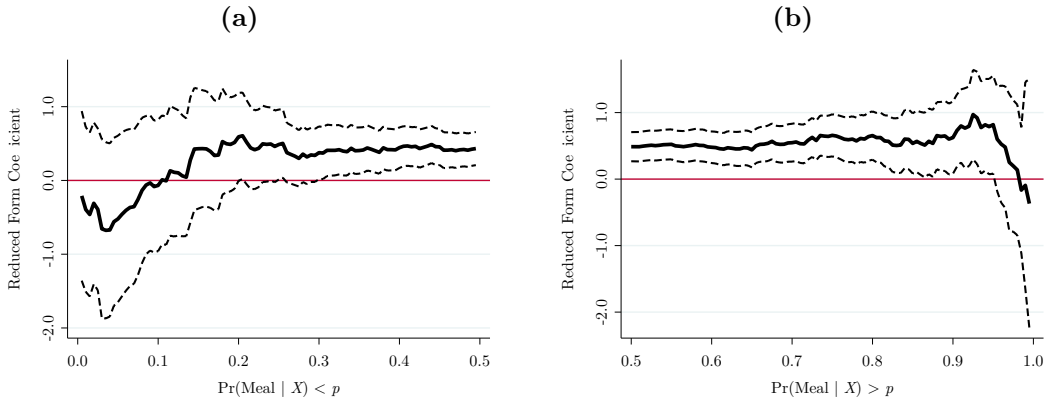
The left panel (a) plots the reduced form coefficients on our instrument index for regressions that include observations with lower and lower meal propensity as one moves to the left on the horizontal axis. At about $Pr(Meal|X) \approx 0.15$, the reduced form effect begins to diminish. The effect also becomes noisier as the sample becomes smaller. Similarly, the right panel (b) plots the same coefficients, but now for regressions with higher and higher

Table 5: Top 50 Variables

X Variable ($Y = jd$ Mean Utility)	Std. Coef	t stat.	X or Z Variable (D = Ever Meal)	Std. Coef	t stat.	Is Z?
Doc, log(cardio claims)	-0.05	16.1	Doc, log(cardio claims)	0.05	14.3	
Doc, Grad. year	-0.02	6.9	HRR, N Doctors	-0.27	9.3	
State, Ad Duration	0.80	6.1	HRR, AMSA	-0.05	7.7	Y
State, Ad Units	-0.77	6.0	HRR, N AAMC affils.	0.09	7.5	
State, Ad Spend	0.02	4.3	Doc, Grad. year	0.02	6.4	
Hosp, N AAMC affils.	0.02	4.1	HRR, Faculty share	0.05	6.3	
Doc, N Specialties	-0.01	4.0	Hosp, N AAMC affils.	0.04	5.2	
HSA, Cadiac hosp. rate	-0.02	3.9	HRR, N Cardiologists	0.11	4.9	
HRR, Faculty share	0.02	3.8	HRR, Uninsured share	0.05	4.5	
Hosp, N Cardiologists	0.04	3.6	HRR, N faculty	0.04	4.3	
Hosp, Admissions	-0.04	3.3	HRR, M.A. eligible	0.05	4.2	
Hosp, N faculty	-0.03	3.3	Doc, Is Female	-0.01	4.2	
HRR, Docs sum cardio. claims	-0.29	3.2	HSA, Cardiologists sum annual claims	0.26	4.1	
HRR, N AAMC affils.	0.03	3.1	State, LIS Part D enroll	-0.04	4.1	
HSA, Docs sum annual claims	-0.19	3.1	HSA, N AAMC affils.	0.05	3.9	
HRR, Docs avg. annual claims	0.36	3.0	HRR, Cadiac hosp. rate	0.03	3.8	
HRR, Docs avg. cardio. claims	-0.35	3.0	HRR, AMSA fac. wgt.	-0.02	3.4	Y
HSA, N AAMC affils.	0.03	2.5	HSA, Cardiologists sum cardio. claims	-0.20	3.4	
HSA, Teaching Hosp. Admission share	-0.05	2.5	Doc, Uses ERX	0.01	3.3	
HRR, N Cardiologists	-0.04	2.4	HRR, Cardiologists sum cardio. claims	-0.20	3.3	
HSA, Docs sum cardio. claims	0.14	2.2	State, Ad Units	-0.52	3.2	
Doc, N Organizations	-0.01	2.1	State, Ad Duration	0.51	3.2	
Doc, Is Female	-0.01	2.1	HRR, AMSA fac.-time wgt., Crestor	-0.02	3.0	Y
State, LIS Part D enroll	-0.02	2.1	HSA, N Doctors	-0.07	3.0	
HSA, N Cardiologists	0.04	2.0	HRR, AMSA time wgt., Crestor	0.04	3.0	Y
HSA, Teaching Hosp. Bed share	0.04	2.0	Hosp, Cardiologists avg. annual claims	0.07	3.0	
Doc, Uses EHR	0.01	2.0	HSA, Uninsured share	-0.03	2.8	
HSA, Uninsured share	-0.02	1.9	Hosp, AMSA	0.01	2.8	
HRR, Docs sum annual claims	0.18	1.9	HRR, Cardiologists avg. annual claims	-0.17	2.7	
HSA, Cardiologists sum cardio. claims	0.09	1.8	HRR, Cardiologists avg. cardio. claims	0.17	2.7	
Hosp, Cardiologists sum cardio. claims	0.06	1.8	HRR, Cardiologists sum annual claims	0.17	2.7	
Doc, Uses PQRS	0.01	1.8	Hosp, Cardiologists avg. cardio. claims	-0.06	2.5	
HSA, M.A. enrolled	-0.01	1.5	HRR, AMSA time wgt.	0.10	2.4	Y
Hosp, Beds	0.02	1.5	State, Ad Spend	0.01	2.3	
HSA, M.A. eligible	0.01	1.5	Hosp, N Doctors	-0.03	2.1	
HRR, N Doctors	0.04	1.4	HSA, Docs sum annual claims	-0.16	2.1	
Doc, Is faculty	0.01	1.4	Doc, AMSA	-0.02	2.0	
HRR, Uninsured share	-0.01	1.3	HRR, Docs avg. cardio. claims	-0.17	1.9	
Hosp, Docs avg. cardio. claims	-0.02	1.3	HRR, Docs avg. annual claims	0.16	1.9	
HSA, Cardiologists sum annual claims	-0.07	1.3	Doc, Uses EHR	0.01	1.8	
Doc, N ZIP codes	-0.00	1.2	HSA, Medicaid shrare	-0.01	1.8	
HSA, Cardiologists avg. cardio. claims	0.04	1.1	Doc, Drive time nearest AAMC	-0.08	1.8	
HRR, N faculty	-0.01	1.1	HSA, AMSA, Crestor	0.06	1.8	Y
HSA, Cardiologists avg. annual claims	-0.04	1.1	HSA, N faculty	0.02	1.7	
HSA, Medicaid shrare	-0.01	1.0	Doc, N Hospitals	0.01	1.6	
Doc, Drive time nearest AAMC	-0.00	1.0	State, Part D enroll	0.01	1.6	
HSA, Faculty share	0.00	1.0	HRR, AMSA fac.-time wgt., Lipitor	0.01	1.5	Y
Hosp, Docs sum cardio. claims	-0.03	0.9	HSA, AMSA fac. wgt., Lipitor	0.01	1.4	Y
Hosp, Cardiologists sum annual claims	-0.03	0.9	Hosp, Docs sum cardio. claims	0.05	1.3	

Notes: Reports the coefficients and t statistics from standardized transformations of variables in regressions using the doctor-molecule level mean utility or whether the doctor is ever a recipient of a meal from the firm producing the branded version of the molecule. "Is Z?" flags the AMSA-based I.V.s used in the meal regressions.

Figure 4: Placebo Test



meal propensity as one moves to the right on the horizontal axis. Here the reduced form drops toward zero after $Pr(Meal|X) \approx 0.95$. Although diminishing sample size at the tails increases noise in the estimates, the results of this exercise are consistent with the validity of our instruments. In particular, they do not show the persistent reduced form parameter estimate that would be expected if our instruments were picking up spurious correlation with some unobserved driver of prescribing.

5.2 Supply Estimation Results

The bottom panel of Table 6 summarizes supply side parameter estimates for the case where $\alpha^{bias} = 1$.[46] For simplicity, we set marginal costs to zero.[47] The most striking feature is the high bargaining parameter estimates for the branded drugs relative to generics. Because the generic sales are aggregated over firms, the bargaining parameters also capture within-molecule competitiveness. This can also be seen in the slightly larger bargaining parameter for generic atorvastatin, where only two manufacturers compete during the first six months of 2012, after which eleven more manufacturers enter. The larger bargaining parameters for Lipitor and Crestor in 2012 reflect the fact that POS prices remain high in many regions for much of 2012 as insurers are slow to adjust formularies, despite the improved outside option with generic atorvastatin entry.[48] Finally, we estimate that the weight insurers place

[46] In the counterfactuals, we recompute the supply parameter estimates for $\alpha^{bias} \in [0, 1]$, and the estimates change on slightly.

[47] As the generic margins are quite small, any reasonable marginal cost assumption would give very similar numbers in our counterfactual analyses. The appendix presents results for other marginal cost assumptions in the range found in prior literature.

[48] One potential caveat to this approach is that we do not observe confidential rebates between plans 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 for Pfizer and AstraZeneca may be biased

on enrollee surplus in negotiations is equivalent to the weight they place on net costs: $\alpha = 1$. This may reflect that enrollees are sensitive at the plan choice stage to formulary inclusion of important drugs, and/or downward bias in our revealed preference measure of enrollees' valuation of statins relative to their true health value (a possibility we address in the next Section).

Table 6: Supply Parameter Estimates

Supply:	Atorvastatin	Lipitor	Lovastatin	Pravastatin	Crestor	Simvastatin
mc	0	0	0	0	0	0
B_{2011}	-	0.50	0.09	0.09	0.56	0.07
B_{2012}	0.17	0.57	0.07	0.07	0.58	0.05

$N = 124,876$ doctor-drug-brand-year observations with standard errors clustered at the doctor level ($N_d = 15,063$) via delete-120 jacknife.

These demand and supply estimates cannot by themselves speak to the effect of payments on pharmaceutical markets. By construction, they measure the effect "holding all else equal", but both prices and quantities may adjust to any policy change. And with the oligopoly structure of the market, these strategic reactions will depend on one another in equilibrium. The next Section analyzes the equilibrium impact of meals.

6 Counterfactual Meal Ban Estimates: Understanding the Equilibrium Welfare Effects of Meals

As discussed previously, the full welfare effect of meal payments from pharmaceutical firms to physicians depends upon how the effects of these payments interact with the distortions from other market imperfections. One such imperfection may be that physicians are imperfectly informed or otherwise biased in their prescribing decisions. To the extent that meal payments facilitate interactions that convey information that improves physician prescribing, they can be strictly welfare improving. Even if payments bias prescribing decisions in favor of the focal drug – whether due to reciprocity, selection in messaging, or selection in which physicians receive meals – this may counteract the downward distortion of quantity due to high prices, improving allocative efficiency and perhaps increasing total surplus. In the case of an oligopoly such as the one here between Lipitor and Crestor, meals may even increase consumer surplus if they result in a more efficient allocation between the two drugs than price competition alone. In this Section, we use our estimated model to consider equilibrium

upward. These unobserved potential rebates are an endemic challenge to research on pharmaceutical pricing. Our counterfactuals should be interpreted as holding fixed these rebate incentives (conditional on changes to demand induced by a meal ban).

prices and quantities under a counterfactual ban on meal payments. Though estimates of the informativeness vs. bias of meals are beyond the scope of our estimation, we can adjust the $\alpha^{bias} \in [0,1]$ parameter to vary the assumption of the extent to which the meal effect is "bias" in physician choice (with 1 being all bias and 0 being all information).[49] Below, we first conduct a detailed examination of a counterfactual ban under the assumption that $\alpha^{bias} = 1$. We then go on to explore how the welfare implications of a ban depend on $\alpha^{bias} \in [0,1]$.

6.1 Welfare: Status Quo vs. Meal Ban vs. Efficient Benchmark

To better understand the economics and welfare effects of payments to physicians, we fix $\alpha^{bias} = 1$ and consider two counterfactual scenarios banning meals/payments from pharmaceutical firms to physicians. The first scenario bans payments and allows all prices and quantities to adjust to a new equilibrium. The second scenario computes equilibrium quantities and prices with banned payments and OOP prices at marginal cost – for the case of $\alpha^{bias} = 1$, this is an efficient static allocation benchmark.[50]

In each scenario, we also calculate several functionals of the equilibrium prices and quantities: retail producer surplus PS_{retail}, which is equivalent to out-of-pocket spending; consumer surplus CS_{retail} implied by the utility model of demand; the component of revealed preference "consumer surplus" driven by meals $CS_{meals} = \sum_{jb \in \mathcal{J}_t} q_{jbdt} \frac{\theta^m}{\theta^p} 1_{\{m_{jbd}>0\}}$ (which we assume to be pure bias in our overall consumer and total surplus calculations); and total point-of-sale transfers from insurers to manufacturers/distributors $POS_{transfers}$. We summarize the welfare implications in two ways: First, we calculate "total surplus" $TS = CS_{retail} - CS_{meals} + PS_{retail} - PS_{meals}$. Here, we net out PS_{meals} (the dollar value of meals to physicians) as a lower bound on the firms' costs of physician interactions, so that TS represents an upper bound on true surplus. Second, we compute an alternative measure of consumer welfare based on estimated health impacts from studies of statin efficacy.

Table 7 displays the results, under the observed data and counterfactual regimes (and separately for each year in order to show how the results depend on market structure). Focusing first on quantities, the primary result is that payments offset the underprovision of statins due to (market power keeping) prices above marginal cost – the quantity of statins consumed with payments (column (1)) almost completely closes the gap between the meal ban case (column (2)) and the efficient benchmark (column (3)). Looking at the two branded

[49] Because supply parameter estimates are a function of $\alpha^{bias} \in [0,1]$, we re-estimate supply for counterfactuals where we vary this parameter. The estimated α^{cs} always remains 1. Bargaining parameters increase slightly as the bias parameter increases, but by less than ten percent between bias equal to 0 and 1.

[50] This is efficient in the sense that it removes any meal or market power pricing distortions. It does not speak to other potential distortions in patient/physician choice or insurer weighting of the implied consumer surplus in price negotiations.

molecules separately, payments bring Lipitor quantity to exactly the efficient benchmark, relative to a ban scenario where they are about 20 percent too low. By contrast, the model predicts that payments cause Crestor utilization to overshoot the efficient benchmark by about 20 percent (though they are also estimated to be 20 percent too low under the ban).

Table 7: Welfare and Counterfactual Estimates ($\alpha^{bias} = 1$)

	2011			2012		
	(1) Obs	(2) Ban	(3) Eff	(4) Obs	(5) Ban	(6) Eff
$Q_{statins}$ (millions)	4.15	3.95	4.14	4.58	4.45	4.59
$Q_{atorvastatin}$	0.95	0.76	0.95	1.43	1.45	1.53
$Q_{Crestor}$	0.66	0.42	0.54	0.71	0.44	0.57
$\bar{p}_{statins}$ ($, OOP)	20.27	18.13	0	14.04	12.10	0
$\bar{p}_{atorvastatin}$	42.58	45.47	0	16.29	15.95	0
$\bar{p}_{Crestor}$	45.55	47.95	0	42.67	43.19	0
PS_{retail} ($ millions)	84	72	0	64	54	0
CS_{retail} ($ millions)	1489	1410	1488	1651	1599	1656
CS_{meals}	-103	0	0	-72	0	0
TS ($ millions)	1469	1481	1488	1643	1652	1656
$POS_{transfers}$	154	128	457	148	117	313

Note: Welfare estimates using data (Obs) and counterfactual equilibrium (Ban and Eff) quantities and prices. All parameters different from zero at 1% level (clustered via delete-120 jackknife at the doctor level). Table with standard errors in Appendix.

Comparing 2011 and 2012 shows the importance of modeling strategic interaction and substitution across drugs. In 2012, after the entry of generic atorvastatin, meals primarily drove substitution to Crestor.

These quantity effects highlight several of the issues motivated in Section 3 and Inderst and Ottaviani (2012). The extent to which payments affect allocative efficiency depends upon their scale relative to the distortion due to high prices, and upon their affect on strategic interactions between the firms. In the market studied here, payments may move total quantity closer to the efficient allocation, but these aggregate effects also play out very differently across individual products in the market. Moreover, translating these quantity effects into surplus measures requires further analysis, depending 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.

Equilibrium prices in the meal ban counterfactual indicate that meals have a relatively small effect on out-of-pocket prices. Interestingly, a meal ban in 2011 does cause equilibrium prices for the branded products to rise somewhat because Crestor's payments make it a closer substitute for Lipitor than it is under the ban, but this effect is modest. In 2012 there is no appreciable price effect of a ban in 2012. The reason for the small price effects

is that the low price sensitivity of demand (and that prices that are often below firm profit maximizing levels due to insurer-firm bargaining) mean that price is not a very attractive tool for capturing market share.[51]

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. If this effect is pure bias, leading to improper decisions (an assumption that seems extreme and is revisited below), this would result in a loss of consumer surplus of $CS_{meals} = -\$103$ million in 2011 and $-\$72$ million in 2012. This could be offset to the extent that payments steer patients towards better treatments – in particular, since two firms have patented drugs in 2011, payments could in principle better align their market shares with their qualities – but the comparison of $CS_{retail} + CS_{meals}$ across columns (1) and (2) shows that this is not the case here. Banning payments results in an increase of \$24M (1.6 percent) in consumer surplus in 2011 via 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 may increase surplus in an efficient manner. Here, we see that producer surplus losses from a ban are slightly smaller than consumer gains in both 2011 and 2012, resulting in total surplus being slightly higher with a ban. It will become clear in the next Section, though, that Total Surplus is higher with meal payments once they are even very slightly correlated with information that improves prescribing.

Another factor to consider is 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 enrollees and, in the case of Part D, the government, and so it is not easily translatable into a per person effect on premiums, let alone welfare. With that caveat, however, the calculations under $POS_{transfers}$ suggest that these drug cost effects are meaningful. Because payments steer patients toward much more expensive drugs, they increase spending on statins by \$26M (20 percent) in 2011 and \$31M (26 percent) in 2012, relative to our counterfactual where payments are banned.

Another result to notice in comparing 2011 to 2012 is the welfare effect of the generic atorvastatin entry. Under the equilibrium in the observed data, this generic entry even increases total surplus by \$174M (12 percent). This is interesting for its own sake, but also as another magnitude to which one might compare the meal payment effects. Statins are highly effective drugs, and this can be seen in the rather large consumer surplus estimates

[51] The result of small counterfactual changes in price is also in part driven by the estimated insurer concern for consumer surplus α^{cs}. For example, lower insurer concern for patients would imply larger supplier bargaining parameters, which would in turn make price more tightly related to supplier profits.

relative to non-statin treatments. This large baseline surplus from statins can make any effect seem rather small in comparison. Using the impact of a major generic entry as a point for comparison can be helpful. In this case of $\alpha^{bias} = 1$, the consumer surplus benefit of a ban on payments is about 14 percent (or counting p^{pos} potentially up to 29 percent) as large as the benefit of generic atorvastatin entry.

6.1.1 A Clinical-Based Measure of Consumer Welfare

Finally, there is the fact that our consumer welfare measurements are based on revealed preference estimates of a utility function that represents doctor/patient choice for statin treatment. While this estimated function has a straightforward interpretation in terms of the choice process driving market demand, it could deviate from a measure of true consumer surplus due to physician agency or physician/patient biases. In light of this, we construct an alternative measure of consumer welfare, CS_{LYG}, by combining our equilibrium quantity predictions with estimates of the health value of statins from the clinical literature valuing "life years gained."[52] Because the health value of statins is so large in the clinical literature, the calculations indicate a large welfare loss from a meal ban relative to any spending considerations.[53]

6.2 Implications of Varying $\alpha^{bias} \in [0, 1]$

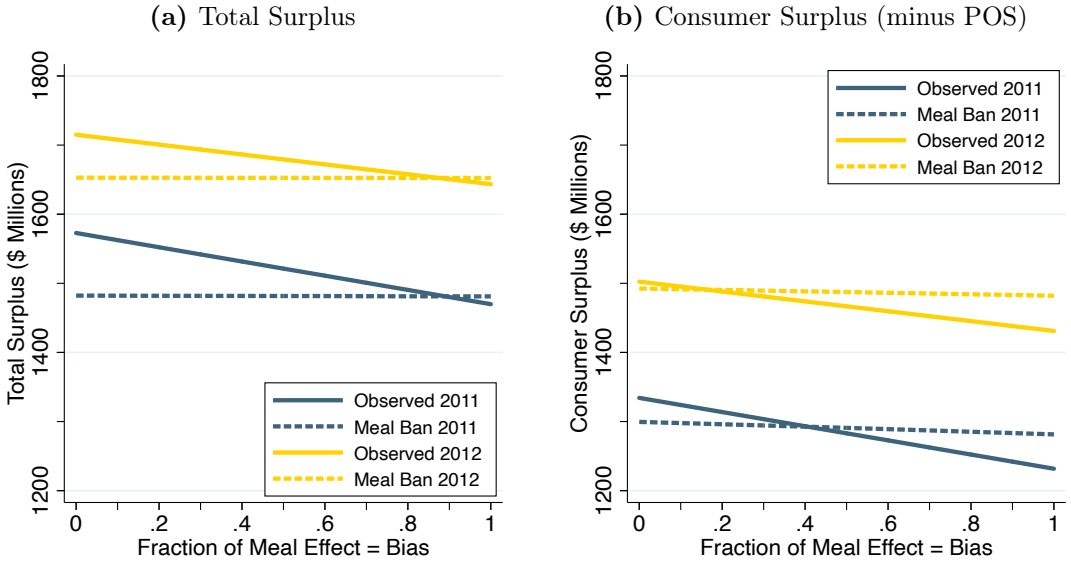
Many pharmaceutical market participants would argue that meal payments and the interactions surrounding them represent at least some information transfer that could improve physician prescribing. The extent of this positive effect, vs. the more ambiguous effects of biasing promotion, is hotly debated, and even experts provide a wide range of assessments. Here we allow the parameter governing this mix, $\alpha^{bias} \in [0, 1]$ (with 1 being all bias and 0

[52] Here, we assume that all prescribing is "appropriate" – i.e., marginal patients are indicated for treatment – up to the efficient quantities with no price or meal distortion. For usage above this, we assign utility value zero. This assumption seems appropriate for drugs like statins, which are generally thought to be underutilized even absent price distortions (see Baicker et al. (2015)). We would urge caution in applying this assumption for drugs that are prone to overutilization, such as opioids (Hadland et al. (2018)).

[53] Our life-years gained calculation is as follows. First, there are approximately 6.93 claims per beneficiary year in the 2013 Medicare Part D Data, the first year that days supply and beneficiary counts are publicly reported; we therefore divide our claim counts by 6.93 in each year. Second, statins are intended to treat chronic conditions and effectiveness will depend on medication adherence; we apply the minimum 37 percent adherence rate from hyperlipidemia trials (adherence rates range from 37 percent to 80 percent) (Deichmann et al. 2006). Third, among our estimated count of adherent beneficiaries choosing moderate statins, we apply the life year gain of 0.69 for Medicare-age enrollees estimated by the Heart Protection Study Collaborative Group (Heart Protection Study Collaborative Group 2009); and for the incremental benefit of the "strong statins" atorvastatin/rosuvastatin, we apply the additional 0.09 life year gain from high-dose atorvastatin vs. low-dose atorvastatin from the TNT study (Wagner et al. 2009). Finally, we apply a conservative value of $75,000 per life year gained (Cutler 2004).

being all information), to vary, and we recompute our welfare estimates for the observed and counterfactual ban equilibria. The results are summarized in Figure 5.

Figure 5: Welfare and Counterfactual Estimates ($\alpha^{bias} \in [0, 1]$)



Looking first at the total surplus implications in the left panel (a), it is clear that the extent of improvement vs. bias induced by meals has meaningful implications for welfare. Once at least 10 percent of the meal effect is correlated with improved prescribing ($\alpha^{bias} < 0.9$), the total surplus impact of meals becomes positive. In the extreme case where meals are fully beneficial ($\alpha^{bias} = 0$), the total surplus improvement from meals relative to a ban is more than half the size of the benefit from generic atorvastatin entry.

Turning to consumer surplus in the right panel (b), the main difference is the threshold α^{bias} at which meals make consumers better or worse off. For consumers in 2011, a meal ban is beneficial whenever $\alpha^{bias} > 0.40$. In 2012, this becomes $\alpha^{bias} > 0.10$.

7 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, and they often take place in conjunction with other distortions due to agency, market power, and strategic interactions between firms. While recent theoretical work (Inderst and Ottaviani 2012) has

shed new light on these tradeoffs, it has remained challenging to identify these relationships empirically, in part because of the strategic targeting of experts by firms. 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 strategy to overcome the challenges of empirically estimating these effects in the health care industry. We show that local academic medical center conflict of interest policies influence the probability of payments from pharmaceutical companies for unaffiliated doctors in the same region. We use this continuous instrumental variable to trace out the distribution of the treatment effects of firm interactions in the market for statins. We also exploit variation in statin drug market structure over time using the Lipitor patent expiration and ensuing generic entry to disentangle market power effects. 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 find the treatment effects of meals on prescribing to be positive and significant, both statistically and economically. The average treatment effect on treated physicians is larger than OLS estimates, consistent with firms targeting payments to physicians who would otherwise have prescribed the focal drug with low probability, but who are highly responsive to meals.

Our counterfactual welfare analysis of banning payments indicates that such a ban would have a positive effect on consumer and total surplus as measured from our estimated demand and supply models. This is the result of two conflicting forces. 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. However, this comes at the cost of higher prices, which outweighs the extensive margin gains. This result is sensitive to the consumer welfare measure, though – if we allow for the majority of treatment effects to be driven by informative interactions rather than physician-induced demand, welfare increases in the presence of meals.

There are limitations in our approach. We focus on a particular 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 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.

References

Abaluck, J., Gruber, J., and Swanson, A. (2018). Prescription drug use under medicare part d: A linear model of nonlinear budget sets. *Journal of Public Economics*, 164:106–138.

Afendulis, C. C. and Kessler, D. P. (2007). Tradeoffs from integrating diagnosis and treatment in markets for health care. *American Economic Review*, 97(3):1013–1010.

Agha, L. and Molitor, D. (2018). The local influence of pioneer investigators on technology adoption: Evidence from new cancer drugs. *Review of Economics and Statistics*, 100(1):29–44.

Agha, L. and Zeltzer, D. (2019). Drug diffusion through peer networks: The influence of industry payments. *NBER Working Paper No. 26338*.

Alpert, A., Evans, W. N., Lieber, E. M. J., and Powell, D. (2019). Origins of the opioid crisis and its enduring impacts. Working paper.

Alpert, A., Lakdawalla, D., and Sood, N. (2015). Prescription drug advertising and drug utilization: The role of medicare part d. NBER Working Paper No. 21714.

American College of Cardiology (2017). Study looks at uspstf vs. acc/aha guidelines for statin therapy. http://www.acc.org/latest-in-cardiology/articles/2017/04/18/15/45/study-looks-at-uspstf-vs-acc-aha-guidelines-for-statin-therapy.

Anagol, S., Cole, S., and Sarkar, S. (2017). Understanding the advice of commissions-motivated agents: Evidence from the indian life insurance market. *Review of Economics and Statistics*, 99(1):1–15.

Baicker, K., Mullainathan, S., and Schwartzstein, J. (2015). Behavioral hazard in health insurance. *The Quarterly Journal of Economics*, pages 1623–1667.

Belloni, A., Chernozhukov, V., Fernandez-Val, I., and Hansen, C. (2017). Program evaluation and causal inference with high-dimensional data. *Econometrica*, 85(1):233–298.

Bernheim, B. D. and Rangel, A. (2009). Beyond revealed preference: Choice-theoretic foundations for behavioral welfare economics. *Quarterly Journal of Economics*, 124(51-104).

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.

Berry, S. T. and Waldfogel, J. (1999). Public radio in the united states: does it correct market failure or cannibalize commercial stations? *Journal of Public Economics*, 71(2):189–211.

Campbell, J. J. (2008). *Understanding Pharma*. Pharmaceutical Institute, Raleigh, NC, 2 edition.

Cardell, N. S. (1997). Variance components structures for the extreme-value and logistic distributions with application to models of heterogeneity. *Econometric Theory*, 13(2):185–213.

Carey, C. M., Lieber, E. M. J., and Miller, S. (2020). Drug firms' payments and physicians' prescribing behavior in medicare part d. *NBER Working Paper No. 26751*.

Chandra, A., Gruber, J., and McKnight, R. (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review*, 100(1):193–213.

Chen, B. K., Gertler, P. J., and Yang, C.-Y. (2016). Physician ownership of complementary medical services. *Journal of Public Economics*, 144:27–39.

Chintagunta, P. and Manchanda, P. M. (2004). Responsiveness of physician prescription behavior to salesforce effort: An individual level analysis. *Marketing Letters*, 15(2-3):129–145.

Clemens, J. and Gottlieb, J. D. (2014). Do physicians' financial incentives affect medical treatment and patient health? *American Economic Review*, 104(4):1320–1349.

ConsumerReports (2014). Evaluating statin drugs to treat: High cholesterol and heart disease.

Cooper, Z., Craig, S. V., Gaynor, M., and Reenen, J. V. (2019). The price ain't right? hospital prices and health spending on the privately insured. *Quarterly Journal of Economics*, 134(1):51–107.

Cutler, D. M. (2004). *Your Money or Your Life*. Oxford University Press.

Cutler, D. M., Skinner, J. S., Stern, A. D., and Wennberg, D. (2019). Physician beliefs and patient preferences: A new look at regional variation in health care spending. *American Economic Journal: Economic Policy*, 11(1):192–221.

Datta, A. and Dave, D. (2016). Effects of physician-directed pharmaceutical promotion on prescription behaviors: Longitudinal evidence. *Health economics*.

Deichmann, R. E., Morledge, M. D., Ulep, R., Shaffer, J. P., Davies, P., and van Driel, M. L. (2006). A metaanalysis of interventions to improve adherence to lipid-lowering medication. *The Ochsner Journal*, 16(3):230–237.

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

Dickstein, M. J. (2016). Physician vs. patient incentives in prescription drug choice. Working paper.

Dranove, D. (1988). Demand inducement and the physician/patient relationship. *Economic Inquiry*, 26(2):281–98.

Dubois, P., Griffith, R., and O'Connell, M. (2018). The effects of banning advertising in junk food markets. *Review of Economic Studies*, 85:396–436.

Duggan, M. and Scott Morton, F. (2010). The impact of medicare part d on pharmaceutical prices and utilization. *American Economic Review*, 100(1):590–607.

Egan, M., Matvos, G., and Seru, A. (2018). The market for financial adviser misconduct. forthcoming Journal of Political Economy.

Einav, L., Finkelstein, A., and Polyakova, M. (2018). Private provision of social insurance: Drug-specific price elasticities and cost sharing in medicare part d. *American Economic Journal: Economic Policy*, 10(3).

Einav, L., Finkelstein, A., and Schrimpf, P. (2015). The response of drug expenditure to nonlinear contract design: evidence from medicare part d. *The quarterly journal of economics*, 130(2):841–899.

Finkelstein, A., Gentzkow, M., and Williams, H. (2016). Sources of geographic variation in health care: Evidence from patient migration. *Quarterly Journal of Economics*, 131(4):1681–1726.

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

Goldman, D., Joyce, G., and Zheng, Y. (2007). Prescription drug cost sharing. *JAMA*, 298(1):61–69.

Gowrisankaran, G., Nevo, A., and Town, R. (2015). Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review*, 175(1):172–203.

Grassley, C. (2009). Grassley works for disclosure of drug company payments to medical groups. https://www.grassley.senate.gov/news/news-releases/grassley-works-disclosure-drug-company-payments-medical-groups.

Grennan, M. (2013). Price discrimination and bargaining: Empirical evidence from medical devices. *American Economic Review*, 103(1):145–177.

Grennan, M. (2014). Bargaining ability and competitive advantage: Empirical evidence from medical devices. *Management Science*, 60(12):3011–3025.

Gruber, J. and Owings, M. (1996). Physician financial incentives and cesarean section delivery. *RAND Journal of Economics*, 27:99–123.

Guo, T., Sriram, S., and Manchanda, P. M. (2019). "let the sun shine in": The impact of industry payment disclosure on physician prescription behavior. Available at SSRN: https://ssrn.com/abstract=2953399.

Hadland, S. E., Cerdá, M., Li, Y., Krieger, M. S., and Marshall, B. D. L. (2018). Association of pharmaceutical industry marketing of opioid products to physicians with subsequent opioid prescribing. *JAMA Internal Medicine*.

Heart Protection Study Collaborative Group (2009). Statin cost-effectiveness in the united states for people at different vascular risk levels. *Circulation: Cardiovascular Quality and Outcomes*, 2.

Heckman, J. J., Urzua, S., and Vytlacil, E. (2006). Understanding instrumental variables in models with essential heterogeneity. *Review of Economics and Statistics*, 88(3):389–432.

Ho, K. and Lee, R. S. (2017). Insurer competition in health care markets. *Econometrica*, 85(2):379–417.

Ho, K. and Pakes, A. (2014). Hospital choices, hospital prices, and financial incentives to physicians. *American Economic Review*, 104(12):3841–84.

Iizuka, T. (2012). Physician agency and adoption of generic pharmaceuticals. *American Economic Review*, 102(6):2826–58.

Inderst, R. and Ottaviani, M. (2012). Competition through commissions and kickbacks. *American Economic Review*, 102(2):780–809.

Johnson, E. M. and Rehavi, M. M. (2016). Physicians treating physicians: Information and incentives in childbirth. *American Economic Journal: Economic Policy*, 8(1):115–41.

Khedkar, P. and Sturgis, M. (2015). For pharma reps, a challenging market for physician access gets even tougher. Accessmonitor 2015 executive summary, ZS Associates.

Kremer, S. T., Bijmolt, T. H., Leeflang, P. S., and Wieringa, J. E. (2008). Generalizations on the effectiveness of pharmaceutical promotional expenditures. *International Journal of Research in Marketing*, 25(4):234–246.

Larkin, I., Ang, D., and Steinhart, J. (2017). Association between academic medical center pharmaceutical detailing policies and physician prescribing. *JAMA*, 317(17):1785–1795.

Levitt, S. D. and Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *Review of Economics and Statistics*, 90(4):599–611.

Manchanda, P. M. and Honka, E. (2009). The effects and role of direct-to-physician marketing in the pharmaceutical industry: An integrative review. *Yale Journal of Health Policy, Law, and Ethics*, 5(2).

McFadden, D. (1978). Modeling the choice of residential location. *Transportation Research Record*, 673.

McGuire, T. (2000). Physician agency. In Culyer, A. and Newhouse, J., editors, *Handbook of Health Economics*. Elsevier.

McGuire, T. and Pauly, M. (1991). Physician response to fee changes with multiple payers. *Journal of Health Economics*, 10:385–410.

Millenson, M. L. (2003). Getting doctors to say yes to drugs: The cost and quality impact of drug company marketing to physicians. BlueCross BlueShield Association.

Mizik, N. and Jacobson, R. (2004). Are physicians "easy marks"? quantifying the effects of detailing and sampling on new prescriptions. *Management Science*, 50(12):1704–1715.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, 46(1):69–85.

Narayanan, S. and Manchanda, P. (2009). Heterogeneous learning and the targeting of marketing communication for new products. *Marketing Science*, 28(3):424–441.

Olssen, A. L. and Demirer, M. (2019). Drug rebates and formulary design: Evidence from statins in medicare part d. Working paper.

Pauly, M. (1980). *Doctors and their workshops: Economic models of physician behavior*. University of Chicago Press.

Pham-Kanter, G., Alexander, G. C., and Nair, K. (2012). Effect of physician payment disclosure laws on prescribing. *Arch Intern Med.*, 172(10):819–821.

Robles-Garcia, C. (2020). Competition and incentives in mortgage markets: The role of brokers. Working paper.

Rochaix, L. (1989). Information asymmetry and search in the market for physicians' services. *Journal of Health Economics*, 8(1):53–84.

Rosenbaum, L. (2015). Reconnecting the dots—reinterpreting industry–physician relations. *New England Journal of Medicine*, 372(19):1860–1864.

Schneider, H. J. (2012). Agency problems and reputation in expert services: Evidence from auto repair. *Journal of Industrial Economics*, 60(3):406–433.

Scott Morton, F. and Kyle, M. (2012). Markets for pharmaceutical products. In McGuire, T., editor, *Handbook of Health Economics*, volume 2, chapter 12. Elsevier B.V.

Shapiro, B. (2018). Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *Journal of Political Economy*, 126(1):381–437.

Sinkinson, M. and Starc, A. (2018). Ask your doctor? direct-to-consumer advertising of pharmaceuticals. *Review of Economic Studies*.

Starc, A. and Swanson, A. (2018). Vertical integration and drug prices. Working paper.

Starc, A. and Swanson, A. (2019). Preferred pharmacy networks and drug costs. Working paper.

Steinbrook, R., Kassirer, J. P., and Angell, M. (2015). Justifying conflicts of interest in medical journals: A very bad idea. *BMJ*, 350:h2942.

United States Department of Justice (2009). Eli lilly and company agrees to pay $1.415 billion to resolve allegations of off-label promotion of zyprexa. https://www.justice.gov/archive/opa/pr/2009/January/09-civ-038.html.

Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives*, 28(2):3–28.

Wagner, M., Goetghebeur, M., Merikle, E., Pandya, A., Chu, P., and Taylor, D. C. (2009). Cost-effectiveness of intensive lipid lowering therapy with 80 mg of atorvastatin, versus 10 mg of atorvastatin, for secondary prevention of cardiovascular disease in canada. *Canadian Journal of Clinical Pharmacology*, 16(2):331–45.

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

APPENDICES – FOR ONLINE PUBLICATION ONLY

A Additional Institutional Background

A.1 Medicare Part D

37 million people, or 70 percent of eligible Medicare beneficiaries, enrolled in Part D plans in 2014.[54] Medicare-eligible individuals can acquire prescription drug coverage through standalone Part D plans or 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. These in turn may be impacted by: prescribers' training and knowledge, interactions with pharmaceutical firms, and preferences over cost control; the relevant drugs' 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 mandates coverage generosity of plans in terms of actuarial value, types of drugs covered, and pharmacy network breadth. Enrollees are entitled to basic coverage of prescription drugs by a plan with equal or greater actuarial value to a standard Part D plan.[55]

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 after patent expiration) have even higher copays or may not be covered by plans at all. On the other hand, 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; maximum copays for LIS enrollees are low or zero.[56]

Part D issuers receive premiums from enrollees and a variety of subsidy payments from

[54] *Hoadley, J., Summer, L., Hargrave, E., Cubanski, J., and Neuman, T. (2014). Medicare part d in its ninth year: The 2014 marketplace and key trends, 2006-2014. Technical report, Kaiser Family Foundation.*

[55] 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").

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

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.[57] Although issuers' strategies and profits are heavily regulated by CMS, they can constrain costs through formulary design (drugs' coverage and placement on tiers, which determine patients' access to those drugs and out-of-pocket costs), negotiations with drug manufacturers, and negotiations with pharmacies.

A.2 Regional Pricing/Formulary Variation in 2012

In our structural analyses, we identify the price sensitivity of demand using panel variation in out-of-pocket prices faced by Medicare enrollees. This variation is driven by Lipitor's patent expiration and by regional variation in insurers' responses to 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.

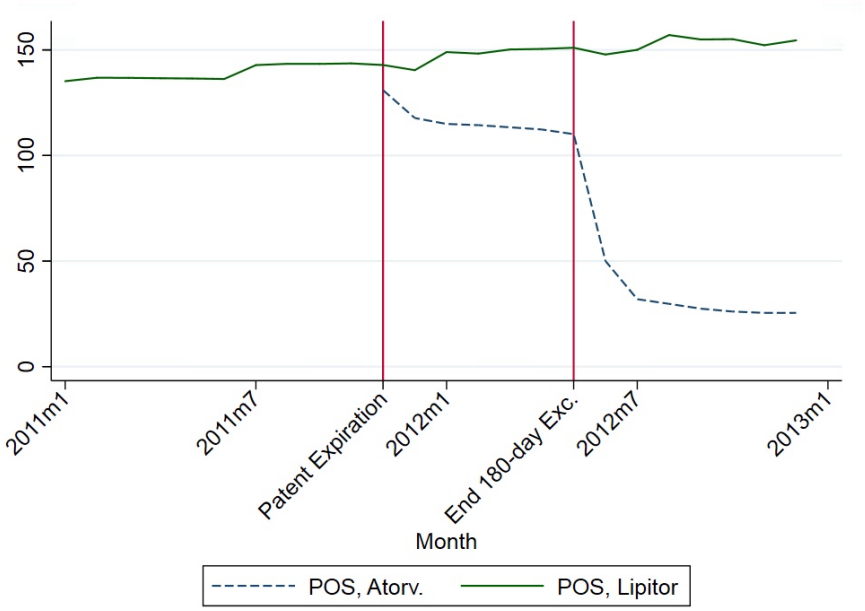
Figure A1 shows the trend in point-of-sale prices for Lipitor and generic atorvastatin over 2011-2012. After Lipitor's patent expired in November 2011, generic atorvastatin was introduced by two generic manufacturers – the "authorized" generic firm Watson Pharmaceuticals and the paragraph IV challenger 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.[58]

Figure A2 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 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

[57] 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.

[58] 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). We return to this issue in our discussion of the structural results.

Figure A1: Point-of-Sale Price of Atorvastatin/Lipitor, 2011-2012



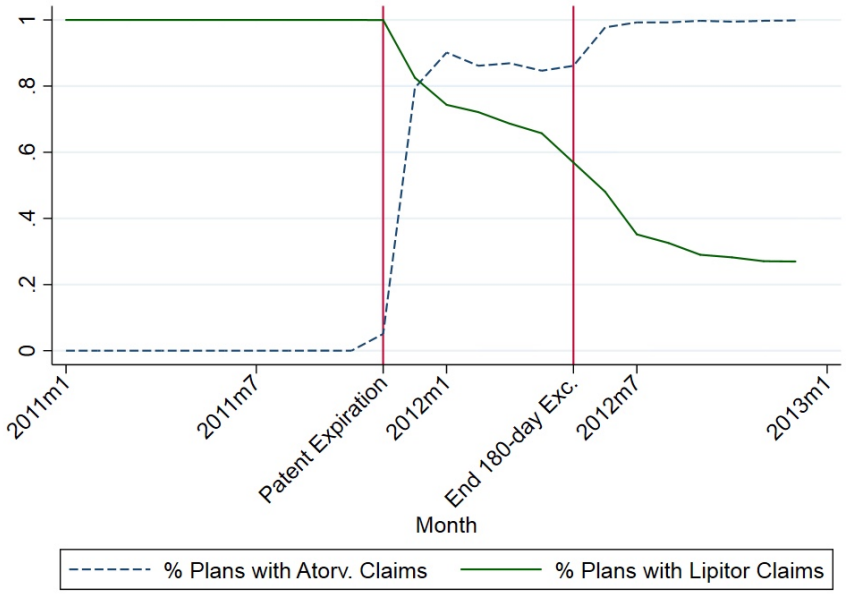
Note: Reproduced from Starc and Swanson (2018). Average point-of-sale price of Lipitor/atorvastatin observed in monthly prescription drug event data. Claims made by non-LIS enrollees for 30-day supply in the initial coverage phase of the drug benefit only.

not remove Lipitor from their formularies until well after patent expiration. As of December 2012, 27 percent of plans still covered Lipitor.

Finally, Figure A3 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 dropped from about $25 to about $9 after 180-day exclusivity. Lipitor copays were 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 39 supersets of states) 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 for 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-

Figure A2: Coverage of Atorvastatin/Lipitor, 2011-2012



Note: Reproduced from Starc and Swanson (2018). Average formulary coverage of Lipitor/atorvastatin observed in monthly prescription drug event data.

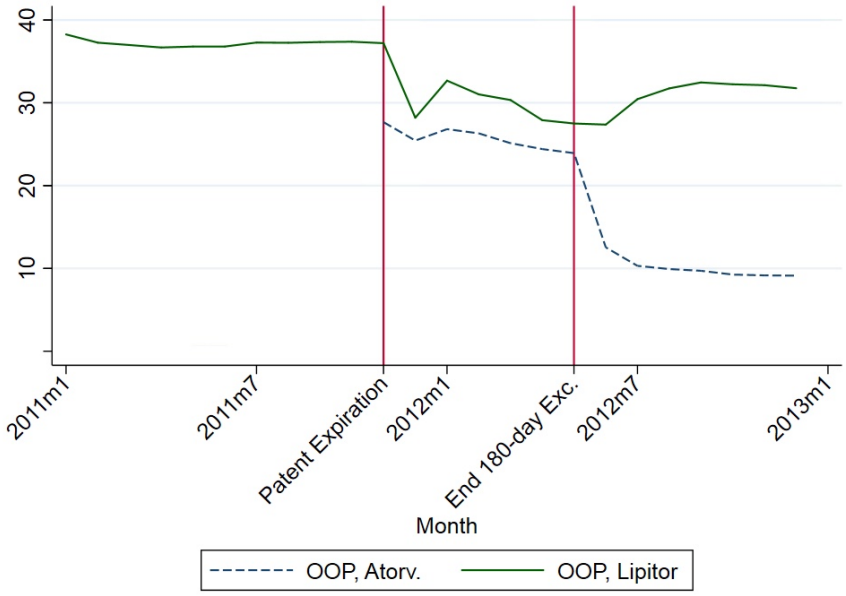
sale price for Lipitor and Crestor were similar in 2012; however, the coefficient of variation on out-of-pocket price increased to 0.19 for Lipitor, and there was substantial variation in 2012 in terms of both point-of-sale (CV =0.27) and out-of-pocket price (CV =0.28) for generic atorvastatin. This price variation is presented for our focal drugs in Table A1 below.[59]

Table A1: 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***

[59]The primary distinctions between Table A1 and Figures A1 and A3 are (1) that the prices in the Figures are claims-weighted, while the prices in the Table are enrollment-weighted across plans; and (2) that the Figures are from claims data and are thus conditional on drugs being covered on plans' formularies. We set out-of-pocket price equal to average point-of-sale price in the relevant region when Lipitor is excluded from a plan's formulary. This results in Lipitor's out-of-pocket price increasing from $38 to $84 between 2011 and 2012. 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 A3: Out-of-Pocket Price of Atorvastatin/Lipitor, 2011-2012



Note: Reproduced from Starc and Swanson (2018). 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. Prices are from claims and are thus conditional on drugs' formulary inclusion.

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 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 A1. There is a strong positive association between the pricing policies of the dominant firms in each region and their pricing policies in other regions – this holds within each year and across years, which we can see in the "first stage" result in the final column that pools years and controls for physician fixed effects.

B Appendix: Payment Data, Construction and Context

B.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,[60] categorization approach,[61] 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 collected these reports as a part of their initiative to analyze physician-firm interactions.[62] 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 A2 summarizes interactions levels for all of the firms, active physicians[63] and years of data we observe. In the focal analysis, we utilize only payments from Pfizer (which owns Lipitor) and AstraZeneca (which 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.[64] To identify those firm-years most

[60] 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.)

[61] 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).

[62] E.g., *Rose, S. L., Sanghani, R. M., Schmidt, C., Karafa, M. T., Kodish, E., and Chisolm, G. M. (2015). Gender differences in physicians' financial ties to industry: A study of national disclosure data. PlosOne.*

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

[64] For anecdotes related to the inaccuracies of these early reports, see: *Ornstein, C. and Weber, T. (2010). In Minnesota, drug company reports of payments to doctors arrive riddled with mistakes. Technical report,*

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 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 result of misreporting and not any dramatic change in firm policies.

Table A2: 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.

B.2 Comparing the Dataset to Post-Sunshine Act Data

As outlined in the main text, the Kyruus-developed physician-industry interaction data we analyze was available due to the fact that Pfizer and AstraZeneca, among other drug firms, released this information prior to the mandatory reporting regulations of the Sunshine Act, which began reporting in late 2013. Because these disclosures prior to the Sunshine Act occurred on an ad hoc basis without any standardized reporting agency (the interaction files were typically posted on each firm's website), it is important to provide evidence that this pre-Sunshine Act data is relatively accurate, e.g. it is not censored or biased in any way that would alter our conclusions. To investigate this, we explored post-Sunshine Act data made available by ProPublica[65], examining trends and distributions under the working assumption that firm-level annual trends in physician payments should be smooth, and within-year distributions of payments should be relatively stable.

Like our Kyruus-developed data, the ProPublica version of the official Sunshine Act data, (available at https://openpaymentsdata.cms.gov), is matched to National Provider

Dollars for Doctors.

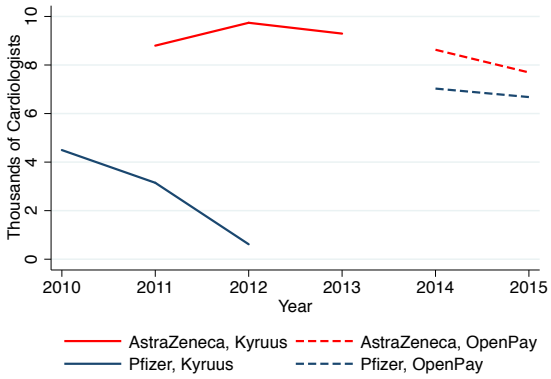
[65]https://www.propublica.org/article/about-the-dollars-for-docs-data

Identifiers. This enables us to hold fixed our set of cardiologists from the main analyses, and compare payments from Pfizer and AstraZeneca in 2011-2012 (from Kyruus) to those in 2014-2015 (from ProPublica).[66]

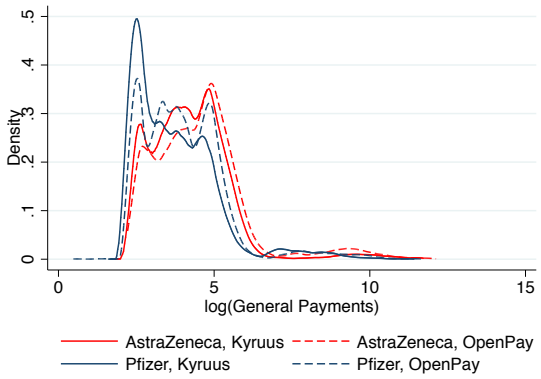
Figure A4 Panel (a) plots the total number of our cardiologists (out of roughly 15,000) that receive any general (non-research) payment from the two firms in each year, based on either data source. In the case of AstraZeneca, the trend is clearly smooth between the two data sources, supporting our assumption that the self-reported data is not notably censored in any way. Although the Pfizer trend line appears to be dramatically different across the two data sources, the spike in 2014 can be explained by the fact that this year marked the approval of Eliquis, a joint venture between Pfizer and Bristol Myers Squibb. Eliquis is an anticoagulant for the treatment and prevention of deep vein thrombosis and pulmonary embolisms, thus cardiologists are the most relevant specialty, and in the OpenPayments data – where, unlike in the Kyruus data, the specific drug associated with each interaction is reported – Eliquis accounts for roughly 60% of the interactions with cardiologists and 78% of total spending on cardiologists. Figure A4 Panel (b) indicates very little variation in the distribution of payment dollar values across the data years/data sources, further supporting the notion that our data is not censored or biased in any significant way.

Figure A4: Kyruus vs. OpenPayment Comparison

(a) Trend in General Interactions



(b) $ Distributions if >0



[66] 2013 is omitted because OpenPayments reporting only includes the last quarter of the year.

C Model Appendix: Additional Theory and Mapping Theory to Empirics

C.1 Meals Equation: Theory to Empirics

Here we show how the theoretical model of meal provision can be simplified to motivate the first stage specification and variables included in our instrumental variables analysis.

We specified that a doctor d would receive a meal from product j whenever

$$(p_{jr}^{pos} - mc_j)\left(q_{jd}^{m=1} - q_{jd}^{m=0}\right) > C_{jd}^{m=1}(N_{jr_d}, \phi) - C_{jd}^{m=0}(N_{jr_d}, \phi). \tag{10}$$

To deconstruct this expression, we use $\partial q/\partial 1_{\{m>0\}}$ as an approximation to $\left(q_{jd}^{m=1} - q_{jd}^{m=0}\right)$.[67]

We also specify a particular cost function $C_{jd}(N_{jr_d}, \phi) = \phi A_{jd}^{-1/\phi} N_{jr_d}^{1/\phi}$. Here A_{jd} represents an access cost shifter that may be product-doctor specific, N_{jr_d} represents the number of other doctors accessed in the region near d, and this function has increasing returns to scale (decreasing marginal costs of access) iff $\phi > 1$. Here we also use $\partial C/\partial N$ as an approximation to $C_{jd}^{m=1}(N_{jr_d}, \phi) - C_{jd}^{m=0}(N_{jr_d}, \phi)$.

Substituting these values gives

$$(p_{jr}^{pos} - mc_j) Q_{jd} \frac{\partial s_{jd}}{\partial 1_{\{m_{jd}>0\}}} > A_{jd}^{-\frac{1}{\phi}} N_{jr_d}^{\frac{1-\phi}{\phi}}. \tag{11}$$

Taking logs and moving variables around a bit then gives something that maps rather cleanly into our linear first stage meals equation:

$$\underbrace{\ln(Q_{jd}) + \frac{1}{\phi}\ln(A_{jd}) - \frac{1-\phi}{\phi}\ln(N_{jr_d})}_{\substack{f(X_{jd};\beta^x) + g(Z_{jd};\beta^z) \\ \text{flexible approx. via LASSO}}} + \underbrace{\ln(p_{jr_d}^{pos} - mc_j) + \ln\left(\frac{\partial s_{jd}}{\partial 1_{\{m_{jd}>0\}}}\right)}_{\substack{\mu_{jd} \\ \text{residual: part correlated w/ } \theta_{jd}^m + \xi_{jd}}} > 0. \tag{12}$$

[67] For our primary demand specification, this partial derivative is given by: $Q_{jd}\theta_{jd}^m s_{jd}\left(s_{jd} + s_{jd|g}\frac{\lambda}{1-\lambda} - \frac{1}{1-\lambda}\right)$

D Additional Tables and Figures

D.1 Summary Statistics

Table A3: Summary Statistics for Select Covariates

X Control Variables	Mean	S.D.
Doc, Drive time nearest AAMC	807.11	1844.45
Doc, Is faculty	0.09	0.28
Doc, Grad. year	1984.5	9.8
Doc, Uses PQRS	0.54	0.5
Doc, N Organizations	1.55	0.84
Doc, AMSA	2.04	7.11
Doc, Is Female	0.08	0.28
Doc, N ZIP codes	1.68	1.72
Doc, Uses EHR	0.63	0.48
Doc, log(cardio claims)	7.47	0.91
Doc, Uses ERX	0.72	0.45
Hosp, Cardiologists sum cardio. claims	37622.98	37534.02
Hosp, N AAMC affils.	4.34	3.61
Hosp, Beds	353.78	345.14
Hosp, Admissions	17530.95	17359.16
Hosp, N faculty	56.01	162.42
Hosp, Docs sum cardio. claims	416012.75	329384.97
Hosp, Cardiologists avg. cardio. claims	2717.24	2286.48
Hosp, N Doctors	382.59	348.88
ZIP, Ad Spend	34121.53	48638.65
ZIP, Ad Units	1075.82	385.09
ZIP, Ad Duration	64446.64	23102.27
HSA, Cardiologists sum cardio. claims	85820.84	158851.61
HSA, Medicaid shrare	21.98	8.52
HSA, N Doctors	1561.15	2349.53
HSA, Docs sum cardio. claims	1091238.75	1692990.5
HSA, M.A. enrolled	23.39	13.76
HSA, Faculty share	0.04	0.02
HSA, Cardiologists avg. annual claims	789.44	4148.72
HSA, N Cardiologists	48.26	84.6
HSA, N faculty	271.68	601.53
HSA, Teaching Hosp. Bed share	0.11	0.19
HSA, Teaching Hosp. Admission share	0.12	0.21
HRR, Docs avg. annual claims	315.06	8648.59
HRR, N Doctors	4621.33	4618.29
HRR, N AAMC affils.	16.13	15.54
HRR, Cardiologists sum cardio. claims	265120.97	322824.78
HRR, Faculty share	0.03	0.02
HRR, M.A. eligible	97920.78	179790.64
HRR, Cadiac hosp. rate	66.37	13.87
HRR, Docs avg. cardio. claims	851.1	23150.11
HRR, Docs sum cardio. claims	4083836.75	4366877.5
State, Part D enroll	9911.14	3671.3
State, LIS Part D enroll	4158.62	1628.28

Z Instrumental Variables	Mean	S.D.
HSA, AMSA fac. wgt., Lipitor	1.94	2.28
HSA, AMSA, Crestor	11.77	12.92
HRR, AMSA	25.62	3.14
HRR, AMSA time wgt.	20849.22	49608.77
HRR, AMSA fac. wgt.	2.43	1.21
HRR, AMSA time wgt., Crestor	9657.84	36104.76
HRR, AMSA fac.-time wgt., Lipitor	1022.99	4758.45
HRR, AMSA fac.-time wgt., Crestor	882.14	4683.61

Notes: Mean and standard deviations for a subset of covariates amongst doctor-molecule observations included in the meal regressions.

D.2 Alternative Graphical Theory

Figure A5: Welfare Analysis with Behavioral Hazard